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Continuous maintenance and the future – Foundations and technological challenges

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ABSTRACT

High value and long life products require continuous maintenance throughout their life cycle to achieve required performance with optimum through-life cost. This paper presents foundations and technologies required to offer the maintenance service. Component and system level degradation science, assessment and modelling along with life cycle 'big data' analytics are the two most important knowledge and skill base required for the continuous maintenance. Advanced computing and visualisation technologies will improve efficiency of the maintenance and reduce through-life cost of the product. Future of continuous maintenance within the Industry 4.0 context also identifies the role of IoT, standards and cyber security.

1. Introduction and motivation

High value products are typically technology intensive, expensive and reliability critical requiring continuous maintenance throughout their life cycle. Continuous maintenance is an engineering service that allows products to achieve required performance through-life with optimum through-life cost. Examples of the high value products include high-tech machine tools, aircraft engine, nuclear power station, train, defence equipment, high-end car, medical equipment, and wind turbine (Fig. 1). In addition, manufacturers are looking for opportunities to provide the maintenance service within the in-service phase of the product life cycle to generate additional revenue and profit. Customers and end users are expecting to pay for the usage of the product rather than the full ownership. This is known as 'servitisation' phenomenon within the manufacturing sector. A full study of the phenomenon under the 'Industrial Product-Service Systems (IPS^2)' CIRP Collaborative Working Group was presented in 2010 [113]. When manufacturers provide continuous maintenance for a product they have developed, especially within an industrial product-service system context, it provides additional opportunities to improve the design and production of those products using the in-service feedback. This can lead to overall reduction of the through-life cost together with reduction in material consumption. There are also new challenges in the area of maintenance service [144] [22] due to the new context. Continuous maintenance of high value products to achieve enhanced durability and reliability is also consistent with the European Commissions recent action plan on Circular Economy [36]. The action plan emphasises on better product design by aligning the producers, users and the recyclers. The new IPS^2 model has prompted additional changes and has become the key motivation for continuous maintenance:

- Engineering for life and extending life of the legacy high value products with optimum cost [7].
- Better understanding of the foundations of product in-service degradation.
- Applying new technologies to improve efficiency and effectiveness of the maintenance: large scale data analytics (or Big Data), automation and autonomy.

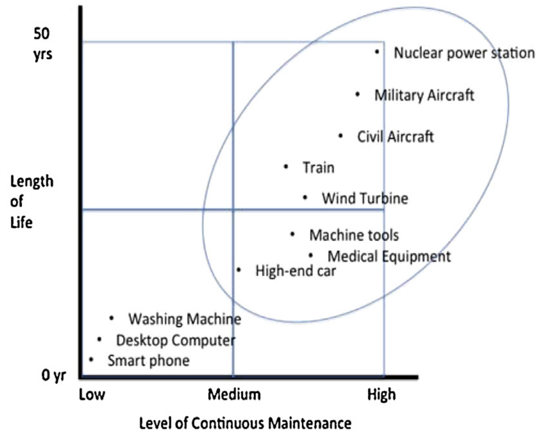

Fig. 1. Scope of the keynote.

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Within next 5 years	Within 5-10 years
Predictive analytics Deep learning 3D printing Virtual/Augmented reality Smart virtual personal assistants Cyber secure manufacturing	Autonomous vehicles Change capable systems Industry 4.0 and servitisation Multi-functional materials IoT/IoE/Wearables Distributed Manufacturing
Beyond 10 years	
Quantum computers Real time prediction of through-life performance Material for long-life Self-configuring production systems Affordable space travel	

Fig. 2. Technological challenges that will affect manufacturing significantly (based on [46,52,180]).

- Applying advanced repair and retrofit technologies for legacy systems.
- Functional improvement of a high value product over time.

With technological developments such as Additive Layer Manufacturing (ALM), Industry 4.0 and Internet of Things (IoT) (Fig. 2) there is a paradigm shift in our ability to better repair or replace individual components, better understand the health of a product and plan maintenance based on the availability of significantly large volume of data. The increasing amount of data collected requires the development of new product-service business models. Whether the collected data belongs to the manufacturer or the customer/user of equipment is a critical issue to be solved when designing the product-service business models. Manufacturers could pay customers for providing the usage data, because with the data the manufacturer improves product quality by feeding back retrieved information in the product development process following the example of "Total Cost of Ownership (TCO)" contracts. The data collection could improve the quality of service received by the customer (as "serviceability") and implement autonomous maintenance approach to reduce the through-life cost of the equipment and increase the customer satisfaction [27].

This keynote presents different technologies and fundamental knowledge that is essential to provide continuous maintenance, their challenges and how the technologies are changing in the future, associated opportunities, uncertainties and risks. The scope of this keynote (Fig. 3) includes continuous maintenance of high value and long life industrial products and the manufacturing facilities for the products within the industrial product-service system context. The keynote will cover technologies that are relevant at component level as well as the whole system level and will also include continuous maintenance approaches used for both workshop-based maintenance and 'in-situ' maintenance of large equipment (e.g., power generation gas turbines). The paper will not consider shorter life products (e.g., consumer products) and will not include retrofitting technologies used to maintain the legacy systems. The keynote does not include 'design for continuous maintenance' or associated product design challenges. This keynote does not also cover the environmental effect of the maintenance and the decision making process for upgrade, overhaul or renewal.

There are several terminologies used in academia and in practice that have similarities with continuous maintenance. The terminologies are Maintenance, Repair and Overhaul (MRO); Through-life Engineering Services; Life Cycle Engineering and Asset Management. The context of this keynote is based on industrial product-service systems and includes several similar terminologies such as product-service systems, performance based contracts, 'power by hour' contracts and availability contracts. Although the terminologies have similarities there are some differences. For the purpose of this paper, the term continuous maintenance is being used in this document. The earliest paper related to computer-assisted maintenance within the CIRP Annals is from 1981 [24]. There are 66 maintenance related papers within the Annals so far with several more papers published within the CIRP Life Cycle Engineering and CIRP Sponsored Through-life Engineering Services conferences. Spur et al. [153] discussed challenges in robotics task execution for maintenance in space platforms, then an extension of the task classification for automation was reported by Farnsworth and

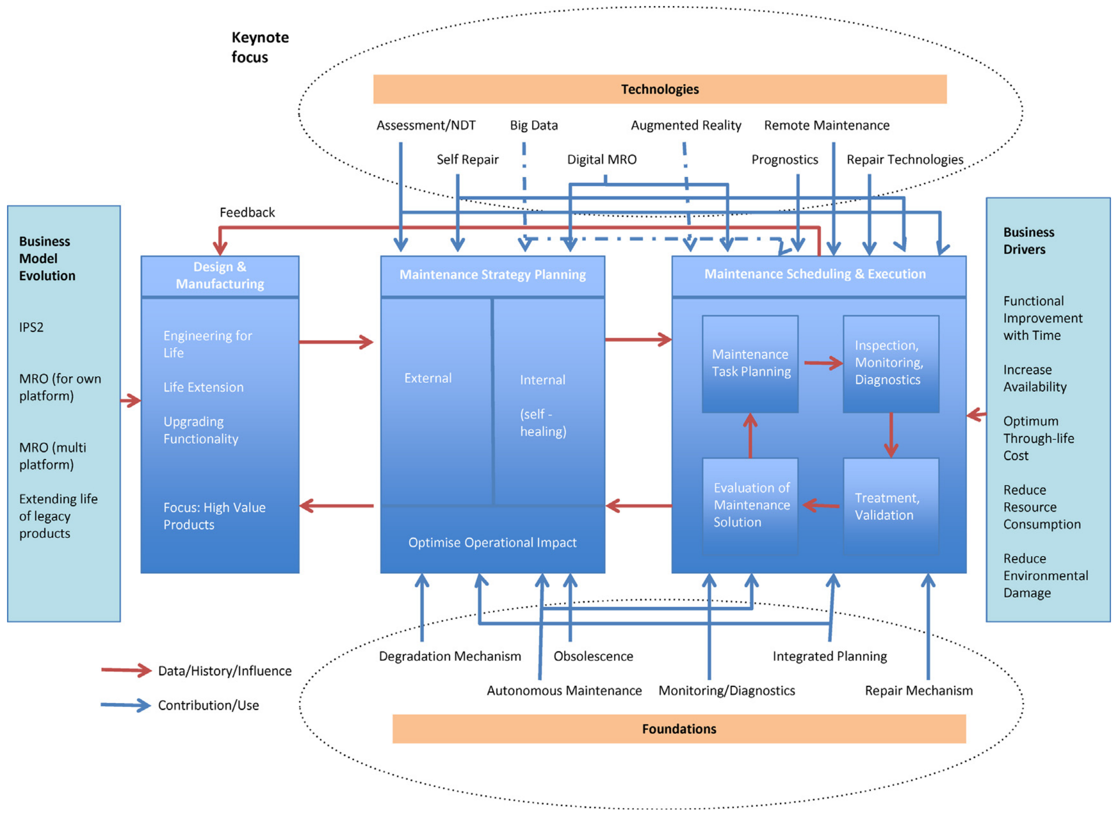

Fig. 3. Continuous maintenance – fundamental knowledge required and technological challenges.

Tomiyama [42]. A number of researchers also reported work on monitoring and diagnostics at the machine tool and the plant maintenance levels [50,107,116,125,126,152,170,182]. Over the years the community has moved on from a component level monitoring to a system level monitoring due to availability of latest technologies, both in terms of sensors and management of data through Clouds. Maintenance planning is another major area of investigation which the community is focused on over the years [11,21,67,76,85,90,94,166,190,201]. The research has evolved over the years from resource-based maintenance planning to whole system planning and optimisation. Model based maintenance has also supported the planning and prognostics research along with a life cycle management perspective [31,77,163,164]. In recent years, study of degradation, automation of maintenance-repair-overhaul (MRO) and virtual reality applications to support maintenance has gained significant interest [78,111,115,122,129,156]. This keynote focuses on the recent technological knowledge challenges at the component and system level and presents major research trends inside and outside the CIRP community.

The keynote is presented in five major sections before it is concluded. After this introduction section, market size of continuous maintenance is investigated across industry within the UK and globally. The next section presents six fundamental knowledge areas that are necessary to develop continuous maintenance solutions. The knowledge types define the current and future technical challenges that are faced in the maintenance tasks. The fourth section focuses on the technologies used in continuous maintenance and their challenges. This section also outlines the use of different technologies across multiple sectors and their limits to solve the continuous maintenance challenges. The suitability of the technologies for equipment used in industrial product-service systems context is also discussed. The fifth section describes future technology trends and investigates new challenges to continuous maintenance. The keynote is concluded in the sixth section with a summary of key technology trends across sectors for maintenance and the major challenges faced to achieve step change in availability of long life equipment with optimum through-life cost.

2. Market size of continuous maintenance

Fig. 4 estimates the global aerospace MRO market is going to be around $89 billion by 2023 (ICF International Analysis report, 2013). The MRO spend growth will be driven by the Asia-Pacific and Middle East sectors. The growth is mainly due to the significant increase expected in the commercial aircraft numbers. Transportation sector (e.g., train) is experiencing significant through-life cost pressures and are also focusing on improving their ‘whole systems approach’ for maintenance of carriages together with the network infrastructure (Technical strategy leadership group, office of the rail regulator, UK, 2014). A recent report on UK service and support industry [112] identifies the global market in ‘service and support’ across high value manufacturing sectors as £490 billion today, growing to £710 billion by 2025.

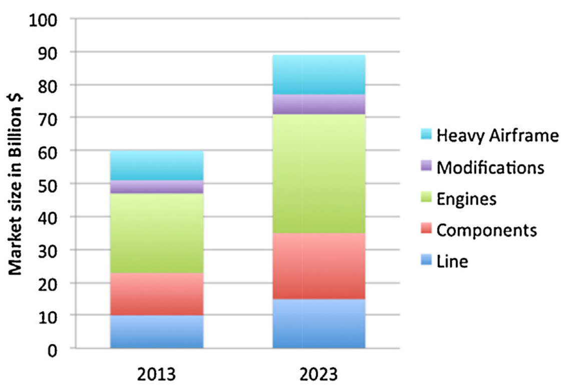

Fig. 4. Global aerospace MRO market in 2023.
Source: ICF International Analysis report 2013.

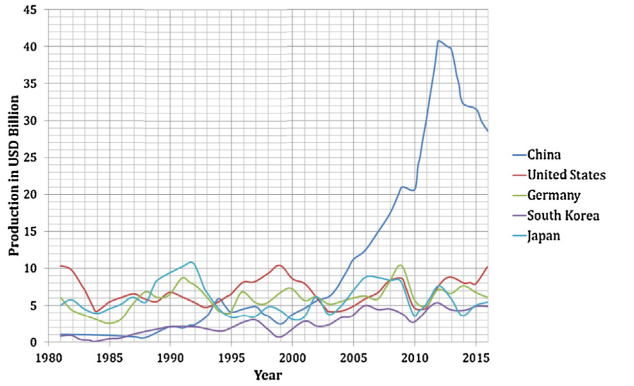

Fig. 5. Consumption of machine tool over the years by top 5 countries. Adapted from [51].

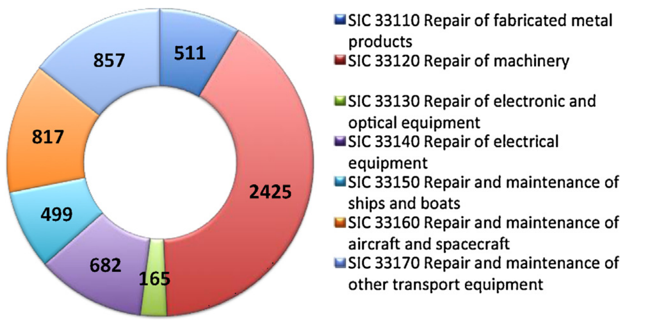

Fig. 6. Number of companies in the UK in the service and support sector, operating by standard industrial classification (SIC) system in December 2014.

Fig. 5 shows the value of machine tools consumed in top 5 countries [51]. Global machine tools consumption value in 2015 was $75,197.5 million. Assuming that the life expectancy of machine tools is typically 14–15 years, the machine tool operating in global market is estimated as worth $500 billion, and is approximately equal to half of the total number of turnouts for the last 15 years. There are no statistics about the global machine tool MRO market, but it can be estimated, assuming spare parts expense occupy 10–15% of the sales of the machine tool manufacturer. Therefore, the estimated market size of the machine tool MRO globally is in the tune of $50–75 billion.

Aerospace, maritime, defence and nuclear sectors dominate the continuous maintenance market. As an example, Fig. 6 shows a breakdown of the number of companies that provide the maintenance service within the UK as of December 2014. Within the aerospace sector, Rolls-Royce has an annual turnover in excess of £14 billion, with more than half derived from the service and support for their products. Their annual costs for providing services are in the order of £5–6 billion. One of their primary company strategic goals is to reduce this cost going forward. Their cost competitiveness in this crucial engineering services market will be the key to future growth, prosperity and profitability. Another example is from Germany, where Fig. 7 shows that, along with the

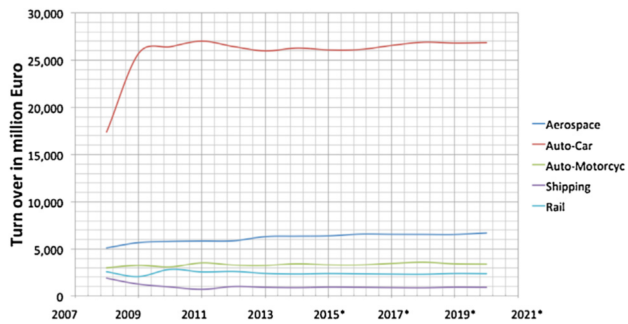

Fig. 7. Size of MRO market across different sectors in Germany (actual values until 2013).
Source: statista 2016.

auto-car sector other sectors are also showing a stable or slightly growing MRO market.

3. Foundations of continuous maintenance

Continuous maintenance is dependent on six fundamental knowledge areas: degradation mechanisms of components and systems in service; repair mechanisms; monitoring, diagnostics and prognostics; autonomous maintenance; obsolescence; and finally an integrated planning.

3.1. Degradation mechanisms of components and systems in service

Modern machines and components are exposed to changing environmental influences and material ageing effects. This results in damages or degradations that needs to be taken care of by using adequate repair and maintenance technologies (Fig. 8). Within the IPS^2 context, replacement or repair of components and systems is a responsibility of the manufacturer often for a fixed price. By developing products that have less degradation the profitability to the manufacturer would increase. This would also mean longer mean time to failure (MTTF), this is in contrast to a previous approach where manufacturers were earning revenue by selling spare parts. Study of degradation mechanisms for the mechanical, electrical and electronics components and systems are not new, but they are mostly limited to degradation of material used against the operating or environmental conditions [37,127,137]. Increasingly manufacturers need to understand how the design and manufacturing features affect degradation as well. Following are few examples of how components degrade and eventually fail and where there is a need for further research. Fig. 9 shows an example of a design parameter affecting the fatigue life of a component [29]. Fig. 10 shows the effect of surface damages (e.g. white layer and material drag), after making a hole in a nickel based super alloy component, on the component fatigue life. Mechanical, Electrical and Electronic systems degrade over time due to use, natural ageing and exposure to environment. The types of degradation include chemical, thermal, mechanical, electrical and radiation. There are two main approaches to model system level failure due to component level degradations: discrete and continuous. Takata et al. [167] has simulated wear (mechanical) of gears and bearings in robot manipulator joints as component deterioration and evaluated the resultant positioning error of an end-effector as functional degradation. In a similar attempt, Iung et al. [78] presented a component level degradation state model based discrete simulation approach to predict the functional failures of a product (Fig. 11). In an attempt to model degradation continuously, dynamic degradation modelling for bearings is developed

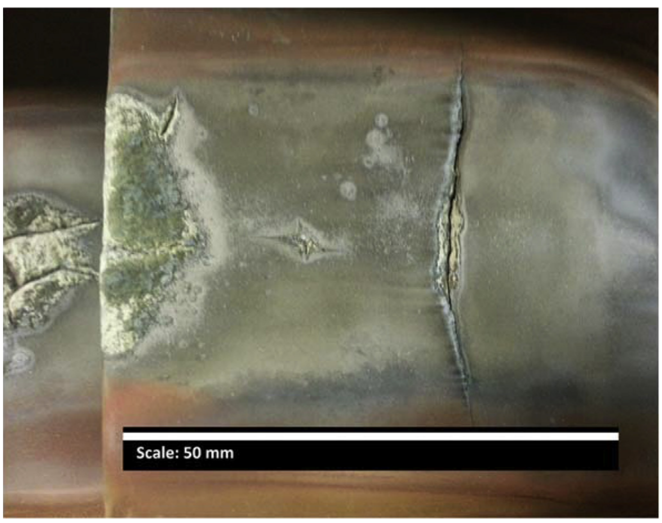

Fig. 8. An image of an aerospace mechanical component exhibiting typical degradations in use, such as cracks, corrosion and delamination [111].

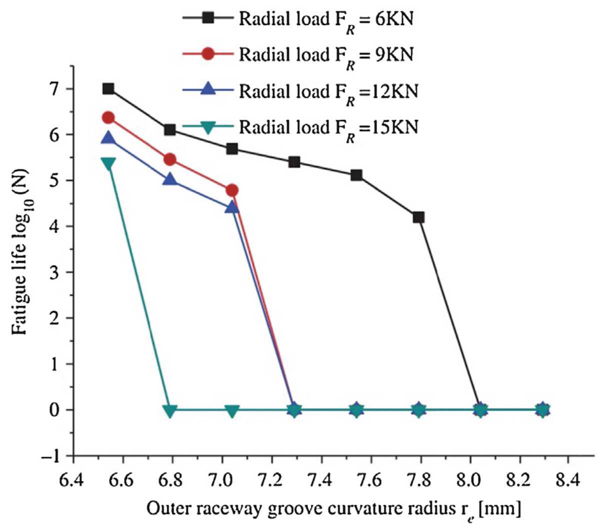

Fig. 9. An example of design parameters affecting fatigue life: effect of outer groove curvature radius of a ball bearing on the fatigue life of outer race [29].

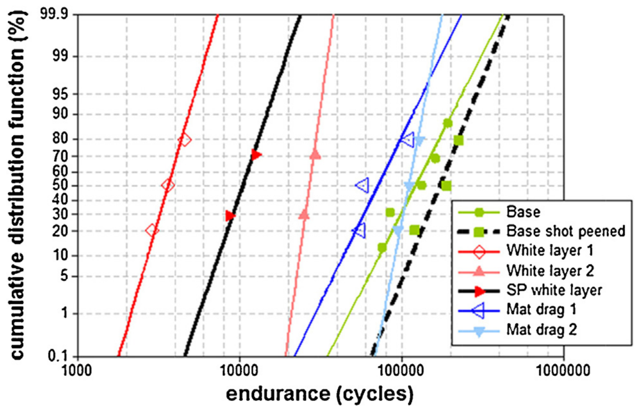

Fig. 10. Surface damages (e.g. white layer and material drag) produced by hole making operation affect fatigue performance (endurance) of the Ni-based super alloy significantly [63].

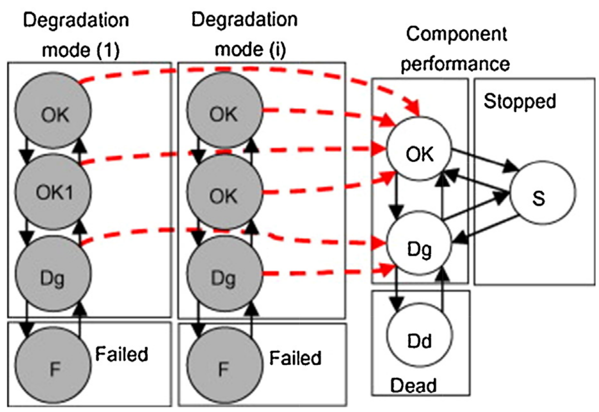

Fig. 11. A mapping approach between degradation mode and the component modes (OK = normal function, Dg = damaged, Dd = dead).

with auto regression models developed from vibration data from sensors. Kalman filter is used to track the model to predict the mechanical degradation of the bearing [135].

Similarly, there is significant interest in understanding the degradation mechanism of electronic components and systems for reliability predictions. Electronic components and systems are often replaced rather than repaired due to low cost of replacement and efficient turnaround. Connectors at system-level failures due to degradations will cause intermittent failures of electronics systems and this is a major challenge for efficient repair of

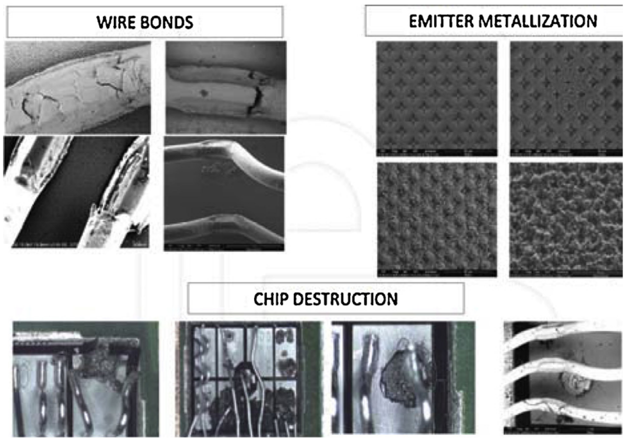

Fig. 12. Major types of degradations in the power electronic modules [150].

electronic systems, especially in quick turnaround scenarios. Electronic system degradation in service could occur at the component, board, line-replacement-unit (LRU) or at the system level. The component-level degradation includes ageing impacted by the environmental conditions, such as temperature, vibration and radiation damage, which will lead to sudden, intermittent or gradual failures. Intermittent faults will lead to what is called 'no fault found' (NFF) problems. A failure is termed NFF when it cannot be reproduced at the testing stage in a laboratory. At the board level, the joints and bond failure due to thermal cycling and vibration is common along with the intermittencies in the performance. The LRU and the system levels often degrade in service through a combination of component/board-level failures with the 'no fault found' type problems. Alghassi et al. [2] identify thermo-mechanical stress as a major factor for connector failures for power electronics, such as isolated-gate bipolar transistor (IGBT). Fig. 12 shows three major types of degradations of power electronic modules as wire bonds, emitter metallisation and chip destruction. There are three major types of failure modes for the wire bonds: heel crack and fractures due to physical constraints on the wires and thermal changes, 'liftoff' due to mechanical stresses generated as a result of different coefficient of expansion between

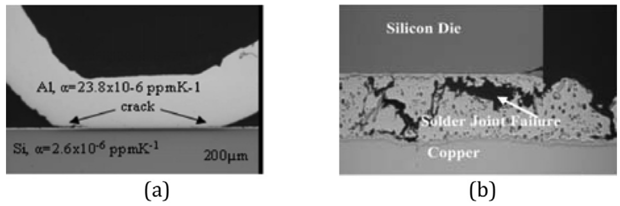

Fig. 13. Bond wire damage due to thermo-mechanical load (microscopic image); (a) breakage and lift-off at the marked area; (b) failure due to bond wire lift-off [120].

Al and Si, and also metallurgical damage due to the thermo-mechanical stress due to the thermal property difference between the Al and Si [150]. Fig. 13 shows microscopic images of wirebond failure and solders failure due to thermo-mechanical loading and stress. Fig. 14 shows the cause and effect for NFF failures in electronic products. It is worth noting the skill level of people and their behaviour also causes NFF failure. There is a need to understand the impact of system architecture and the components on the probability of NFF so that the failure mode can be reduced and can be made predictable with better accuracy.

3.2. Repair mechanisms

Repair mechanisms are versatile. Prevalent principles are separating, joining, coating and cleaning technologies for mechanical products. For electronics soldering, wiring and re-balling for Ball Grid Array (BGAs) are used. Mechatronics components are often substituted in case of damage. A potential future technology for spare part production is Additive Layer Manufacturing that allows producing directly from 3D scan data [3,47,103]. The mechanism involves cleaning the damaged area, depositing new material (Fig. 15) or replacing any component and then machining the geometry through a finishing operation [101]. While there are several approaches to repairing metallic components, repair of composite material is still a major research topic. The composite failure mechanism is still less understood [87] due to unique properties of composite materials. Bonded composite repair is the most common approach to repair structural composite parts. One of the main challenges in the process is to achieve the joint strength and avoid human error. The joint strengths can be

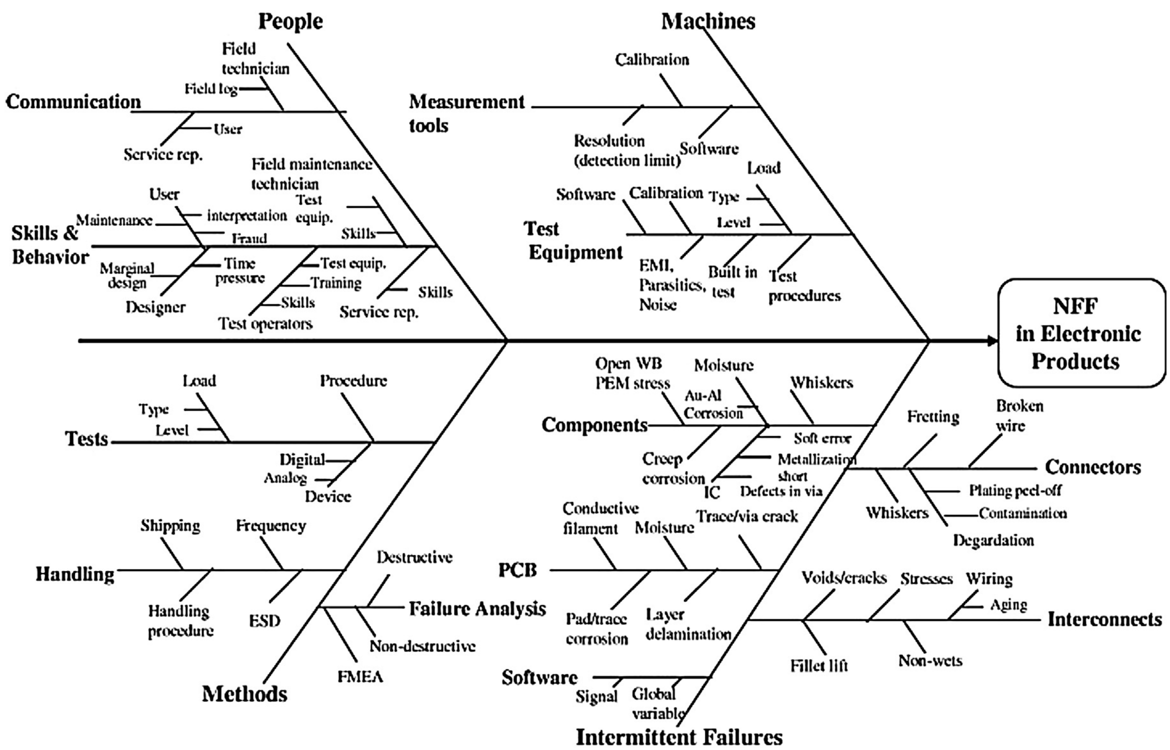

Fig. 14. An example cause and effect diagram for No-Fault-Found (NFF) conditions in electronic products [134].

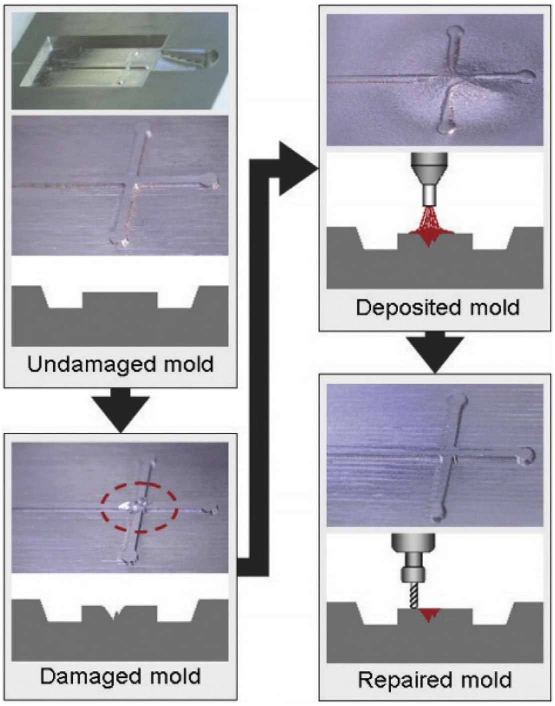

Fig. 15. The process to repair a mould using cold spray deposition and then machining [101].

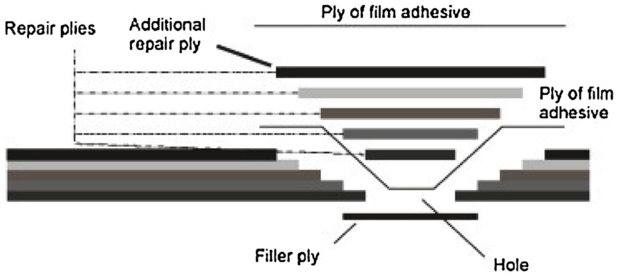

Fig. 16. Laser-based repair of CFRP [45].

improved by designing the repair section for a shear dominant stress state and induce minimum peel stresses in the adhesive layer [58]. Fig. 16 shows laser based repair concept of composite parts with precise layer-by-layer removal of the damaged area [45]. There are attempts to automate the repair process as well to improve efficiency [174] and reduce human error. Part of the composite parts repair process is to assess the damage more accurately (moving from qualitative assessment to quantitative assessment) using advanced techniques like active thermography, digital shearography and laser ultrasonics [87,111].

3.3. Monitoring, diagnostics and prognostics

Monitoring of machines to check their state of degradation due to use or health parameters (e.g., temperature and vibration) is done either using an additional network of sensors [39] or by analysing signals which are available in machines (e.g., position, speed and drive current consumption) [182]. Diagnostic and prognostic tools are classified into two major categories based on how the monitoring data is analysed and the conclusions reached: data-driven and model-based. Sensor based monitoring example is a Health Usage and Monitoring System (HUMS), first used in helicopters. The system records vibration measurements taken at different critical components using different sensors and stores in a removable memory for further diagnostics. Fig. 17 shows a proposed remote monitoring and maintenance system for machine tools [116], where a simple mobile phone based communication is established to connect 8000 machine tools for the remote

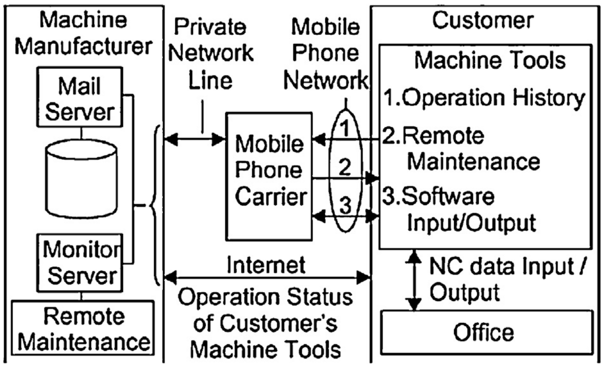

Fig. 17. A remote monitoring and maintenance system for machine tools [116].

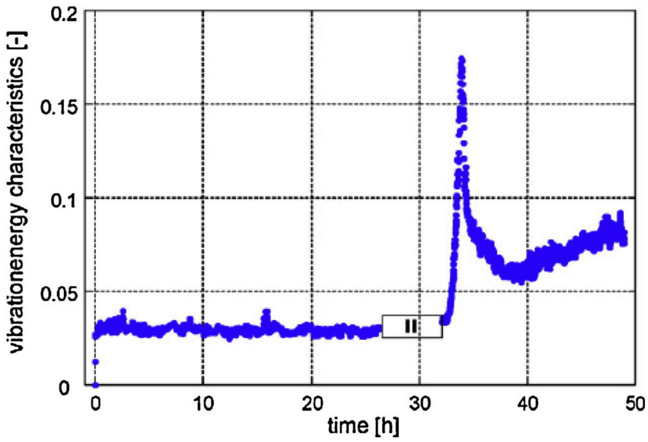

Fig. 18. Effect of wear (2nd half) on vibration energy parameter over time [182].

maintenance. Verl et al. [182] presents a sensor-less monitoring of machine health by analysing the positional error and vibration energy in a drive system (Fig. 18). Dependency of the sampled data on the speed in case of a rotating machine is eliminated through the integration of complex wavelet transform-based envelope extraction of speed-varying vibration signals with computed order tracking [186]. Lanza et al. [95] have also proposed a dynamic optimisation of preventive maintenance schedule using actual operating life of components. The research uses a stochastic technique based on Weibull Cumulative Damage Model and multiple service related stress profiles (e.g., mechanical, thermal and humidity stresses) to predict the remaining useful life of the component. A Bayesian learning based prognostics is also proposed by Ferreiro et al. [44] to reduce the maintenance cost. Uncertainty in measurements is a major source of inaccuracies and therefore a challenge for the condition monitoring. Similarly, there are major challenges in the diagnostics and prognostics in terms of simplicity of the assumptions used during the model development, effect of the operating conditions on the heuristics and data driven models, and also lack of knowledge while extrapolating for the operational envelope.

The work on prognostics should, in summary, address:

- The type of results expected. It is remaining useful life (RUL), a future situation or behaviour and a risk concerning the appearance of future failure modes.
- The abstraction level for which the result is expected – at the component/subsystem/system level.
- The degree of confidence to be associated to the result (e.g., uncertainty).
- The data from which the prognostics results will be calculated. It means data/information related to the past, current or future usage/mission/situation of the item to be analysed. The future can be defined from degradation laws, contextualisation, etc.

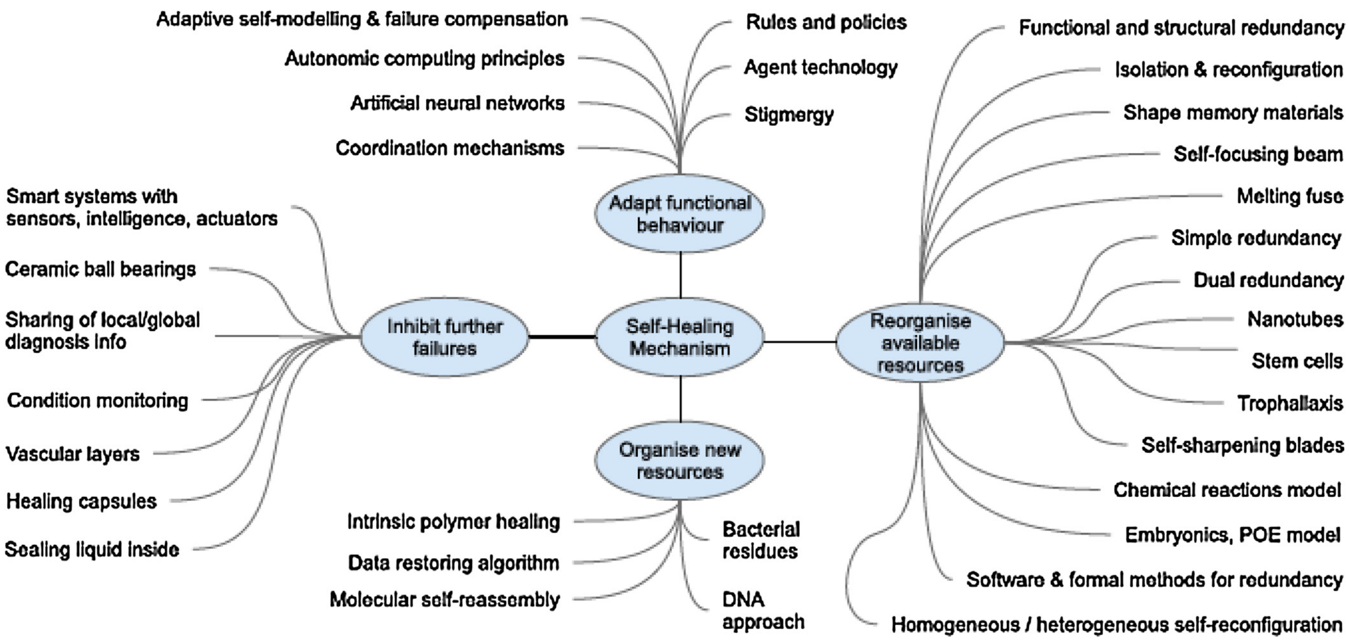

Fig. 19. Categorisation of mechanisms for self-healing and self-repair [48].

- The method/tool to be used for performing projection/forecasting from the data/information available.

3.4. Autonomous maintenance

Automating the continuous maintenance of machines can lead to significant reduction in through-life cost. The automation could come from inherent resilience of a system or a component or could be assisted using external agents, such as robots. The resilience is often achieved at the hardware and software level using self-healing and self-repairing technologies. Self-healing is a bottom-up approach, where the components of a system heal the damage internally. Whereas, self-repair is a top-down approach, where the system is able to maintain or repair itself [48]. In both these cases the system exhibits a degree of autonomy. On the other hand, maintenance efficiency could be improved by using automation (e.g., using robots to support maintenance tasks). Fig. 19 shows categorisation of self-healing and self-repair technologies. Farnsworth and Tomiyama [42] identified key challenges in using robots to assist maintenance as: maintenance is often irregular, non-uniform, non-deterministic and non-standardised. In their research, they proposed building blocks of maintenance tasks and automated the tasks using a standard robot. Effective automation of maintenance tasks would require further co-ordination between robots and advances in autonomous robotics.

3.5. Obsolescence

A component becomes obsolete when it is no longer available from the original manufacturer or its authorised supplier for an affordable price [141]. For long life equipment the risk of obsolescence can come from electronic components, materials, software, mechanical components, test equipment, processes, skills, and documents [146]. The drivers for obsolescence include technological development and commercial decisions to phase out some products. With the performance based contracts (or industrial product-service systems) becoming more popular, the obsolescence risks are found to increase with the manufacturers rather than the customers. The manufacturers are now more interested to design equipment to reduce the impact of obsolescence. A key capability to manage obsolescence and reduce the through-life cost is the ability to predict component procurement life [145] and also to predict the cost of obsolescence resolution [142,143] Effective continuous maintenance of long life systems will require a systematic and proactive approach to manage obsolescence [113].

3.6. Integrated planning

Maintenance planning is a major capability to perform continuous maintenance. Houten et al. [68] identified the product data model to support a model based maintenance planning. An integrated maintenance-planning platform was proposed by Iung et al. [75] that connects different parts of an enterprise to support the maintenance planning, as shown in Fig. 20 [167]. Arnaiz et al. [6] presents a methodology of predictive maintenance technologies that is integrated with specific business scenarios and upcoming technologies. Optimisation of preventive maintenance schedule and spare parts supply is proposed using a stochastic algorithm that uses a load-dependent reliability model [94]. Takata et al. [165] have proposed three feedback loops (Fig. 21) for maintenance management, combined with maintenance planning. Managing life cycle data across the enterprise and decision support is essential for an integrated maintenance planning capability

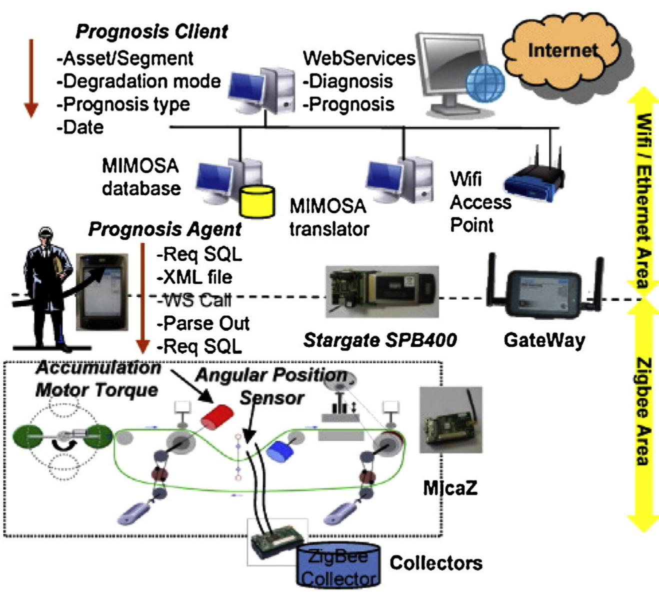

Fig. 20. An e-maintenance framework showing different parts of the technology used, called TELMA [75].

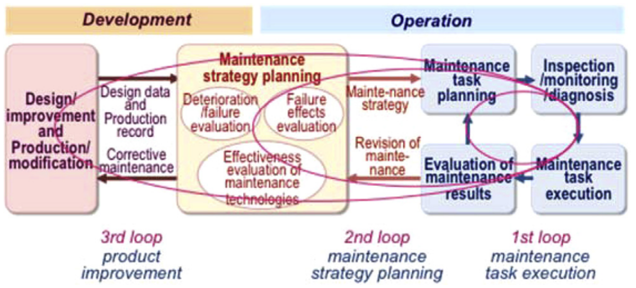

Fig. 21. A framework for life cycle maintenance with three feedback loops [165].

[126]. Colledani et al. [20] have integrated manufacturing system maintenance performance with the productivity to implement a comprehensive continuous improvement. There is a significant need to integrate the production and maintenance considerations for the manufacturing planning and scheduling.

4. Technological challenges

Key technologies that support continuous maintenance, utilising the six knowledge types mentioned above, can be classified as: non-destructive evaluation (NDE) for degradation assessment, repair technologies, prognostics, self-healing and self-repair technologies, remote maintenance, digital maintenance-repair-overhaul (MRO), big data and visualisation of maintenance tasks (e.g., using augmented reality) for planning and training.

4.1. Non-destructive evaluation for automated degradation assessment

Assessing degradation of a component in service using non-destructive evaluation techniques and automating the assessment process are two major trends in continuous maintenance. The techniques used for the degradation assessment include: visual inspection, dye penetrant inspection, magnetic particle inspection, ultrasonic testing, eddy current inspection, X-radiography, photo-luminescence piezo-spectroscopy and thermography [92,181]. Although there are several techniques already used in assessing in-service degradation, thermography is becoming popular in recent years for their ease of use and affordability [196]. Thermography is a rapid, large area inspection, low-cost and non-destructive evaluation technique that is performed by directing an infrared camera at a target (i.e., a component with in-service degradation) and recording a heat map image (also known as a thermogram) of the specimen in order to detect variations in temperature emitted by the component or transmitted from behind it. These changes can reflect a change in temperature or in the material's thermophysical properties, either of which can be exploited to seek assessment of the in-service degradation. There are two main types of thermography: passive and active. Based on the sources and nature of energy for active thermography, there are six different types: pulse [188], lock-in/modulated [131], pulse phase [72], vibrothermography/thermosonics [43], eddy current [199] and laser spot thermography [17]. Thermography is mostly used in studying thermal behaviour of manufacturing operations. Mehnen et al. [111] presents the use of thermography to quantitatively measure the in-service degradation assessment for aerospace components (Fig. 22). Inspection of this component's cooling at various locations indicated differing behaviour of coating close to spalling, indicating sub-surface delamination. The research then proposes to use an image processing approach to measure the shape and size of the delamination. Future work involves improving the quality of the size measurement and performing similar active thermography on in-accessible areas. Inspiration for Fig. 23 has been drawn from non-destructive testing or NDT comparison charts already in use for training purposes that are available online. Further details have been added based on literature and understanding of working concepts of the techniques. Where a statement is unclear due to a

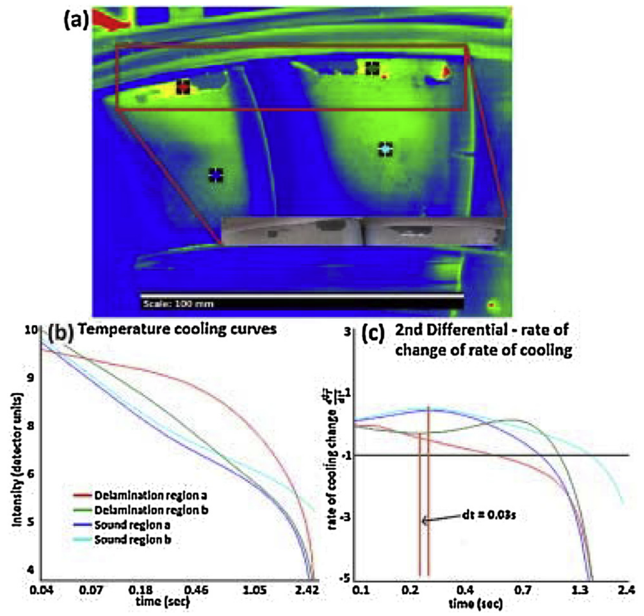

Fig. 22. Inspection of coating delamination indicated by red and green plots in the thermogram on an aerospace component (a), with sound coating plotted for comparison (blue). Logarithmic temperature cooling curves (b) show heat obstruction from delamination, with 2nd differential indicating the time of peak cooling rate change (c) [111].

lack of suitable examples available to demonstrate, a question mark has been applied. For example, it has been suggested that laser stimulation can be used in pulsed thermography to deliver a well-controlled heat injection. While this would facilitate detection of planar sub-surface damages, demonstration of this in practice is not yet sufficient to arrive at this conclusion. The Fig. 23 functions as 'rule of thumb' guidance, and is based on a combination of proven applications and subjective interpretation of capability from conceptual understanding of the techniques only. The figure clearly identifies Ultrasound, X-ray and pulsed thermography having the widest range of applications for metallic components. Fig. 24 also presents a mapping between the key types of mechanical degradations in different industrial sectors and corresponding commonly used NDT techniques to identify them based on literature review [88,92,93,136,162]. Mehnen et al. [111] has presented the suitability of pulsed thermography for automation to improve repeatability of the assessment and increased efficiency. Thermography is more effective for composite part degradation assessment [105]. The major limitations of pulsed thermography are:

- Not well suited to closed degradations that are still adjoined, a break in material to provide change in thermal property is required.
- Not well suited to cracks propagating normal to the surface, change in material must be through-depth.
- Small damages are harder to detect with increased depth.
- Heat-trapping subsurface features such as voids, air pockets and structural channels obscure similar size features below them.
- Thermography inspection requires absorption and re-emission of the injected heat, which requires a high emissivity value at the surface, so is not well suited to reflective metallic surfaces; a coating is required in this instance.

4.2. Repair technologies

Regarding repair and overhaul strategies, different approaches exist [173,179]: starting from single repair events that can be handled by replacement with spare parts up to complete overhaul strategies combined with facelifts and modernisation of machines [172]. Different technologies are needed to fulfil the necessary

Flaw type	Example	Visual	Magnetic particle	Dye penetrant	Eddy current	Ultrasound	X-ray	Pusled Thremography	Laser spot thermography*	Vibro thermography *	Eddy current thermography *
Suface breaking linear	Surface crack	3	1	1	1	3	3	4	1	1	1
Surface breaking volume	Corrosion pit	1	1	1	1	1	1	3	2	4	1
Near surface linear, normal orientation	Near surface crack	4	2	4	1	3	3	3	4	2	1
Near surface linear, parallel orientation	TBC Delamination	4	4	4	4	1	4	1	4?	4?	4
Near surface volume	Void or TBC delamination	4	2	4	1	1	1	1	4?	4	1
Subsurface, linear, normal orientation	Subsurface crack	4	4	4	4	3	3	4	4	4	2
Subsurface, linear, parallel orientation	Sub-surface delamination (applies to composites)	4	4	4	4	1	3	1	4	2	4?
Subsurface volume	Void or subsurface structure	4	4	4	4	1	1	1	1?	4	3
Thickness measurement of thin material	Wall thickness	4	4	4	1	1	1	1	1	4	4
Thickness measurements thick material	Wall thickness	4	4	4	1	2	3	2	2	4	4
Coating thickness measurement	TBC thickness	4	4	4	1	2	3	1	1?	4	4

Fig. 23. A comparison of strengths of non-destructive evaluation (NDE) techniques for degradation assessment in metallic aerospace components, highlighting thermographic strengths. The suitability of techniques against various damage and defect types have been graded 1 (appropriate) to 4 (inappropriate).

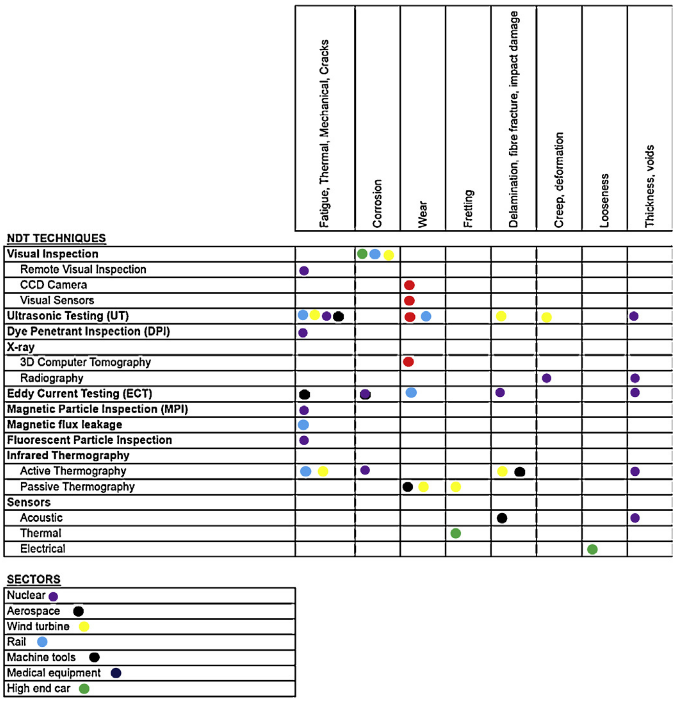

Fig. 24. Mapping of key types of mechanical degradations in different sectors and the most commonly used NDT techniques.

requirements. Especially in the field of cost-intensive and long-living machine tools complete exchange of major components can often be too expensive to keep machines in business [177]. Automated repair [70,159] is a major trend to avoid human errors associated with the manual process, along with the repair of novel materials. Robot guided reworking of functional areas and rapid manufacturing of spare parts is becoming popular [9,140]. Furthermore it is necessary to significantly reduce the production stoppage. This correlates with the productivity of machines and the costs of repair processes. To cover all repair cases a flexible and robust process chain consisting of inspection, repair and remanufacturing technologies as well as quality control is needed [18,160]. Additionally, mobile technologies offer advantages compared to stationary technologies, because there is no need for disassembling and transportation of damaged parts. Repair tasks can be processed in different repair plants or in situ where the large part is directly inspected. Another important requirement addresses the consumption of resources and energy efficiency aspects corresponding to repair and overhaul technologies. A potential future technology for spare part production is additive manufacturing that allows parts production directly from 3D scan data [171,175]. The important repair technologies are presented as below [178].

4.2.1. Cleaning technologies

Cleaning technologies are not only used for better look but also as a preventive measure to maintain functionality. Many of those

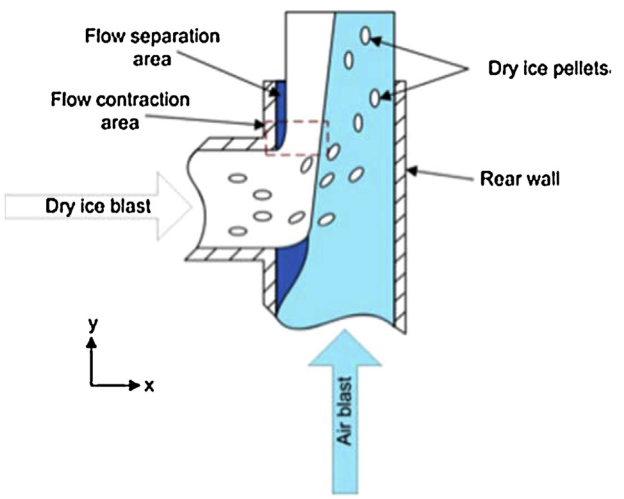

Fig. 25. Dry ice injector principle for cleaning [176].
Source: Fraunhofer IPK.

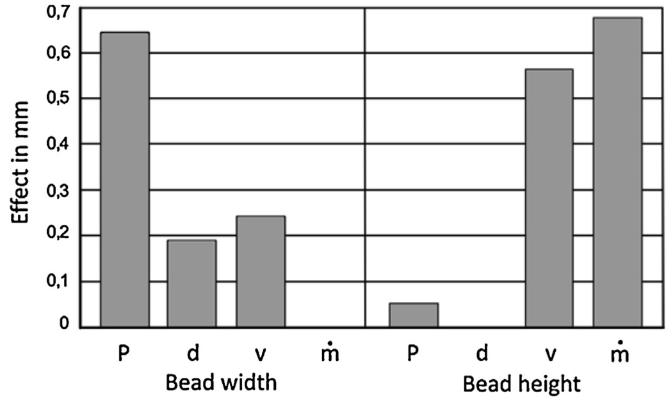

Fig. 26. Effect of welding parameters (power – *P*, spot diameter – *d*, welding velocity – *v*, powder mass flow – *m*) on bead width and height, nickel-based superalloy [53].

principles are using chemicals that have a negative environmental impact. Thus, the application of flexible and eco-efficient cleaning processes has taken on greater significance. In addition, newly developed and adjusted cleaning technologies are able to reduce downtimes, because they can be either used during machine operation or need short time compared to other repair technologies [159].

Dry ice blasting is a dry cleaning technology that causes no residues (Fig. 25). Dry ice pellets are used as an abrasive for blasting processes. They are solid at ambient conditions with a temperature of −78.5 °C and change directly into the gaseous state during blasting. Due to its low hardness, it is suitable for gentle cleaning and processing of sensitive surfaces. Unfortunately the low hardness makes the pellets sensitive to external impacts or friction. Dry ice blasting is predominantly used to clean easily accessible surfaces. For areas with limited accessibility, different blasting nozzles are available [154].

Besides blasting technologies other cleaning technologies are wet cleaning (e.g., ultrasound), mechanical cleaning (e.g., blow off) and thermal cleaning principles [130]. For printed circuit boards principles without electrostatic effect can be used such as ultraclean water, compressed carbon dioxide, blowing, suction or brushing; the major challenge is to reduce adverse environmental effect [104].

4.2.2. Coating technologies

So-called "patch processes" have been established for the repair of engine and turbine components. Damaged component areas are identified and replacements are attached. Subsequently, the contour is re-established with mechanical procedures. Laser metal deposition as an example is a technology to create a metallurgical bonded material deposition on a substrate. It can be used to repair worn surfaces or to produce a hard facing layer [10]. A laser beam is used to melt the surface of a specimen and a powdery filler material is injected in the molten pool [54,132]. The low metallurgical impact is particularly important for preservation of material's microstructure (e.g., high-strength steels) [53,102].

For proper use knowledge about process parameters and their influence on weld bead geometry is necessary [98]. This influence is shown in Fig. 26, using a nickel-based superalloy as example [53]. While bead width is mainly determined by laser power, main effects for bead height are welding velocity and powder mass flow. This knowledge allows adjusting the bead geometry for the specific repair task, e.g., high and narrow weld beads for tip repair.

A future challenge is to develop mobile laser metal deposition solutions. Laser metal deposition is used for metallic materials or composites consisting of carbides in a metallic matrix material, typically tungsten carbides or titanium carbides are used. An example is given in [66], where titanium carbide is used together with an Inconel 718 metal matrix to improve wear performance.

4.2.3. Additive manufacturing technologies for making spare parts

Additive manufacturing technologies mostly follow a customised single part production principle. They are advantageous compared to conventional production technologies like milling, drilling or casting, because they are not limited to conventional design guidelines [171]. They allow production of organic freeform geometries as well as undercuts and multipart production in one step. Polygon data in STL format generated by 3D scanners can be used as direct input for these manufacturing principles. Examples for additive manufacturing and rapid prototyping principles are Selective Laser Melting (SLM) [149], Stereo-lithography (SL), Fused Deposition Modelling (FDM), Wire and Arc Additive Manufacturing (WAAM) [57,185] and Laminated Object Manufacturing (LOM). A future challenge is to overcome material and microstructure limitations to enable better functionality e.g., better surface quality, better dimensional and geometric distortion control, better fatigue strength and increase reproducibility. Furthermore, the process has to be accelerated for use in serial production (e.g., SLM is relatively slow process). General Electric (GE) is going to enter series production of fuel nozzles using SLM and is supposed to manufacture more than 100,000 additive parts until 2020. First projects in Germany like BMBF and AutoAdd even focus on small series in the automotive industry. Another goal is the support of multi-material production, which would allow producing conventional assemblies as single parts (Fig. 27).

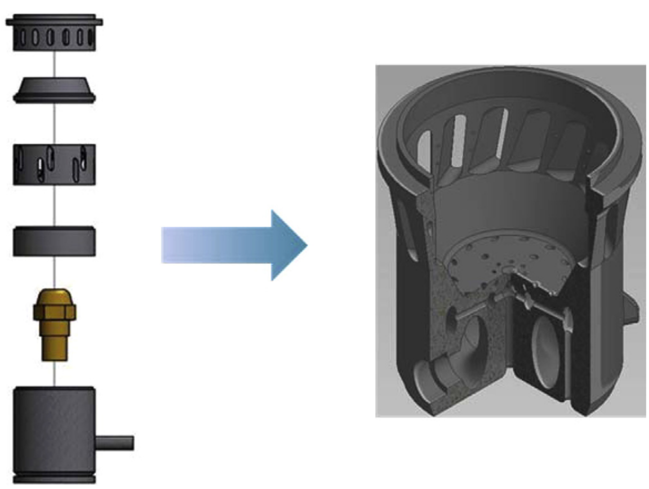

Fig. 27. Example for SLM optimisation: An assembly consisting of 8 parts and different materials were redesigned and produced with SLM as one single part.
Source: Euro-K GmbH in cooperation with Fraunhofer IPK.

4.3. Prognostics

In the past, maintenance was regarded as repair work. Machines were operated until they broke down, and there was no way to predict failures. With the development of reliability engineering in the 1950s, the concept of preventive maintenance was advocated, and time-based maintenance (TBM) was introduced [165]. Reliability centred preventive maintenance [82] and performance centred maintenance [184] are introduced in recent times. In order to realise preventive maintenance, several different approaches have been done. Several papers researched model based prognostics, which is simulation of degradation process. A maintenance decision-making tool using Bayesian Dynamic Networks (BDN) was proposed [79]. Two Remaining Useful Life (RUL) tools were proposed: the component RUL (RULc) and the function RUL (RULf) were researched in order to improve the prognosis efficiency [78]. Kara [86] has also proposed a novel approach to predict the RUL based on history of a part and remaining technological life. It is very difficult to simulate a degradation process therefore there are not many industrial applications. The functional integration of maintenance within the product life cycle, based on experience obtained from work was introduced [26]. Odds approach was also proposed for the integration of the maintenance at the production planning stage for developing opportunistic maintenance task keeping conjointly the product – production – equipment performances [76]. Sensing technologies are often used to predict system failure.

Technologies used for prognostics can be applied at the component and system level. Fig. 28 presents a prognostics process as part of a system level prognostics and health monitoring. At component level, the focus is:

- A direct tracking of the degradation by calculating Reliability/RUL from a degradation modelling based on processes such as Gamma, Markov, Wiener and by taking into account usage and contextualisation. It implies to have at disposal data for parameter calculation [151].
- An indirect tracking of the degradation by using COX model to calculate the RUL [71].

The historical data, i.e., historical signals or indicators, is used to extrapolate the current trajectory of the component observed. It could be done by working on a mono-dimensional health index (Relevance Vector Machine tool) [191] or multi-dimensional health index (Match Matrix tool) [83]. Fig. 29 shows an application of self-organising map technique to classify the different degradation states of bearings.

On the other hand, at the system level, the focus is on the performances/services expected at the system level and represented by the evolution of the properties of each flow (ex. product, energies) [78] produced by the system. Embedded prognostics and self-repair capability could also support more resilient systems.

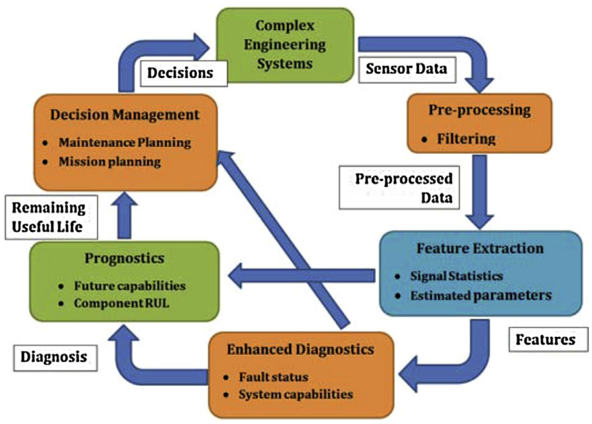

Fig. 28. Prognostics process within PHM loop.
Adapted from: PHM Society.

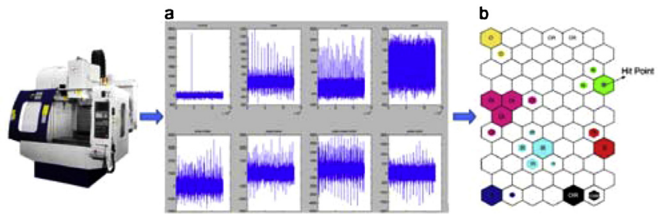

Fig. 29. (a) Vibration signals from bearing degradations and (b) health map for different bearing failure modes using a self-organising map [100].

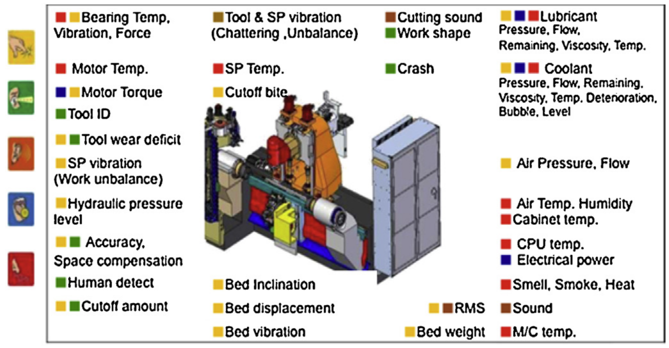

Fig. 30. Different sensing technologies used in Machine Tools.
Source: DMG MORI Co. Ltd.

Fig. 30 shows the different sensing technologies used in machine tools today. The sensing technologies cover component and system level feedback and support the evolution of the system level information. This evolution is built from a functional/dysfunctional analysis allowing a link to be made between the component level and the system one through the flows exchanged between the different functions at different levels together with the propagation of the component degradations at each level. In that way, it is possible to propose a generic pattern for prognostics, which could be applied at different abstraction levels [183]. For example, from the instantiation of this generic pattern to a specific system, it is proposed to create a Dynamic Bayesian Network (DBN) and to combine it with an event model (creating a set of "event" DBN variables that correspond to the degradation (a) and maintenance (b) events) [79] in order to adjust the parameters given a priori with the real value of the parameters. The final prognostics model is resulting by combining the two models [118].

The system level focus continues to be on

- The concept of fleet: the prognostics are calculated in line with similar situations already known and stored in knowledge base. It is supported by Ontologies [110].
- The types of interactions between the components (ex. redundancy, functions distribution and criticality). The prognostics is using the models developed at the component level but by considering the relative weight of each component and the interactions within the co-variables [33].

Some of the key prognostics challenges are:

- The prognostics aims at calculating RUL, but this calculation is very different with regards to the component technologies addressed because the degradation laws are sometimes difficult to model.
- The prognostics are using data/information produced by the monitoring, health assessment and diagnostics upstream processes. The mastering of these processes in terms of robustness, precision; quality of the raw data consumed are key issues to be addressed.
- Uncertainty in the input data and as a result the degree of confidence on the prognosis is still a major challenge. There is also uncertainty associated with the model developed. Changes

in the process, equipment or the environment can all introduce uncertainty that further complicates the RUL calculation.

In order to support environmental and economic sustainability through maintenance services, recently prognostics techniques developed for health prediction are also used to predict the energy consumption and environmental impact [74].

4.4. Self-healing technologies

Self-healing technologies are used for autonomous maintenance. Self-healing can be achieved in materials, in the electronic components and in the software [48]. Thakur and Kessler [169] have presented a review of self-healing polymer nanocomposite materials. Harrington et al. [60] have studied a number of case studies on the biological archetypes for self-healing material development. In a recent development, Nair et al. [121] presented the circuit board integration of a self-healing mechanism to repair open faults by physically restoring fractured interconnects in the electronic circuits. Significant research is required to mature this field before it could be directly useful for continuous maintenance. In parallel, research must develop techniques for qualification of the self-healed state for certification purposes. There are three examples of self-healing technologies under development: self-healing MEMS, self-healing robots and fault tolerant sensor systems that are relevant for continuous maintenance.

4.4.1. Self-healing MEMS

MEMS devices can be very cheap on its own, but can have significant impact on the overall availability of the system where it is used. There is a strong motivation to improve robustness of the MEMS for more resilient systems. There are two principal ways to develop the self-healing capability, one by using redundancy and the other protecting the MEMS device from damage using surface lubrication. Self-healing MEMS accelerometer has redundant gauging finger modules. With a built-in-self-repair strategy, when one module becomes damaged a circuit connection control mechanism replaces the damaged module by a redundant one, as a result improving the robustness of the MEMS device [193]. Applying lubricants in between silicon oxide surfaces to reduce friction could also reduce the in-service degradation of the devices (Fig. 31). The lubrication along with the redundancy could develop next generation of robust MEMS devices [69].

4.4.2. Self-healing robotics

Self-healing in robots is often achieved through re-configurability, modularity, redundancy and adaptive behaviour. Reconfiguration or self-repair by replacing a failed module with another functionally homogeneous module is the most common approach. A number of self-configuring robots already exist [157]. Following the idea of redundancy, the solar-powered Odysseus [109] also performs self-repair on the fly. That is the aircraft will be able to autonomously modify its body while rejecting any failing modules. Odysseus is a project within the DARPA Vulture programme, aiming at an aircraft, which can remain airborne over a duration of five years. Another radically different self-healing capability in a

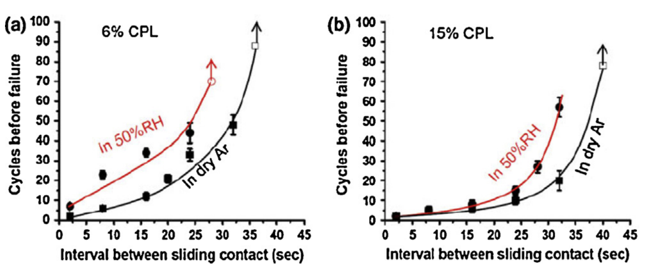

Fig. 31. (a) MEMS degradation: Cycles before failure of 6% cationic polymer lubricant (CPL) in dry and 50% relative humidity (RH) as a function of time interval between cycles, (b) cycles before failure of 15% CPL in dry and 50% RH as a function of time interval between cycles [69].

robot is about modifying its internal model of itself to the changing state of its body, and thus to find alternative ways to maintain its functionality. For example, a walking robot which loses a limb will modify its gait to still be able to walk [13].

4.4.3. Fault tolerant sensor systems

Fault tolerant sensors that are used in systems for monitoring along with the actuators in feedback loops helps the system to self-adapt, which is a step in the direction to achieve self-healing [80]. This self-adaptation allows the system to correct any minor deviations (may be due to the in-service degradation) automatically and autonomously. Brandon et al. [16] have presented an integrated approach to sensing and self-healing for structural health management of deployable structures (e.g. on the moon). A passive wireless sensor network is used in conjunction with self-healing materials, identifying any damage to the structure, monitoring the self-healing process and raising an alert for major damages for human expert intervention. Verification and validation of the sensor network robustness is still a major challenge.

4.5. Remote maintenance

Remote monitoring and diagnosis was discussed considerably in the 1970s, when the technology for data transmission via telephone line was first developed. Although many machine tool manufacturers offered remote maintenance service at that time, this type of service had not become popular due to the immaturity of the technology [165]. Currently, machine tool shipments are growing year after year. This trend is expected to continue for the foreseeable future. Currently, whenever problems occur with machine tools, service technicians are likely to visit the customers' plants to troubleshoot and resolve them. To deal with this situation, the first step is to improve product quality to reduce the number of potential service calls. The second is to increase the efficiency of the service itself. In order to do so, the ideal solution is to acquire the customers' machine tools operating status, perform diagnostic and analysis remotely at manufacturers' service base and conduct necessary preventive maintenance immediately online. In the 2000s remote maintenance with mobile phone technologies was developed and applied by several machine tool manufactures [116]. Remote maintenance with mobile phone structure is shown in Fig. 17. DMG MORI and other machine tool companies around the world have already installed remote maintenance system for several thousand customers' machines. Successful remote maintenance would require data communication across the Extended Enterprise. The remote maintenance is mostly at the level of accessing the health parameters of a machine remotely and perform software-based repair and upgrade tasks.

Another approach for remote maintenance is to use remotely controlled robots to perform maintenance tasks within uncertain environments. Use of remote controlled robots for maintenance is widely used in Nuclear [106], space and any hazardous industries. Fig. 32 is showing a concept maintenance system for nuclear installation, the manipulators are to be operated remotely. The existing remote maintenance technologies work best when the environment is very structured and the state of a machine is less uncertain. Researchers have used Virtual Reality based training systems for the remote maintenance operator training [12]. In an effort to explore use of robots for autonomous maintenance, Fransworth and Tomiyama [42] have proposed a novel task classification for automation and collaborative robot application.

4.6. Digital MRO

Digital MRO comprises all Maintenance, Repair & Overhaul (MRO) activities facilitated by IT-solutions. There is a need to develop new processes, methods and tools for MRO applications, in order to exploit the potential of virtual technologies for MRO optimisation in practice. For instance, solutions for fast access to information on important lifecycle phases and MRO activities,

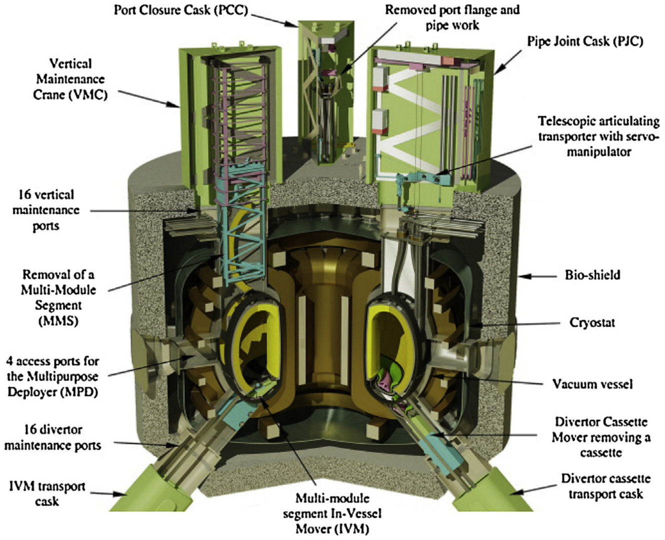

Fig. 32. Section of proposed DEMO vertical maintenance system architecture with remote controlled manipulators [106].

solutions to interface conflicts between various multi-player systems, or to enable remote-servicing with mobile tele-cooperation devices via narrow-band connection are addressed [155]. Different kinds of IT systems are used for scheduling of MRO tasks, resource planning and communication. Predominant IT-Systems in Germany (for example) are self-made or customised software solutions as well as Microsoft Office applications, because the diversity of MRO business makes it difficult to develop a single solution that fits to all requirements:

- Management of inspection plans, protocols and reports
- MRO tasks: Administration, planning, cost control and documentation
- Asset management: Machine data, handbooks, check lists, warranty information, inspection intervals, service contracts, date of purchase, predicted lifespan
- Stock management: Administration of spare parts and availability, tools, aids and expendable items
- Statistics and analysis: Number of MRO jobs, date of inspection, run time information
- Reports for continual improvement process
- Comparison of planned and actual data.

Computerised maintenance management systems (CMMS) aim to cover all of these requirements. However, these systems are costly and need training for use. In case Enterprise resource planning systems are used, CMMS may be an add-on or an integrated part. As a general rule companies are using diverse IT-systems simultaneously without adequate interfaces and with the problem of redundant data. Furthermore, systems are neither integrated horizontally with customers, suppliers and OEMs nor integrated vertically with MES (Manufacturing Execution System), SCADA (Supervisory Control and Data Acquisition) or PLC (Programmable Logic Controller). Besides IT-solutions product design data and technical documentation are important for functional understanding, repair and overhaul. Unfortunately technical documents like bill of material and design drawings or data as well as maintenance protocols are hardly available for maintenance companies that are not from the original equipment manufacturer (OEM) [41]. Product changes are unknown if different companies maintain the same product one after another. An additional issue is around obsolescence of components [198]. Highly experienced staff is needed to perform these tasks [55] and IT-Infrastructure has to enable acceleration of innovations. Modern 3D scanning technologies deliver 3D models of actual product geometry and allow deviation and tolerance analyses in case of available reference models. However, optical limitations and difficult part disassembly make 3D digitisation still a laborious task which is followed by a high effort in data post-processing [156].

4.6.1. Major scientific and technological challenges

The scientific challenge is to create a digital MRO solution to provide all information, data and knowledge that is needed for MRO planning and execution. Of course there are restrictions of data and information exchange between life cycle stages, B2B and B2C relations due to business models and intellectual property rights that can only be solved by new product-service systems [113]. Technical solutions are needed for monitoring, retracing, determination and prediction of product state to optimise the schedule for the MRO operations. Intelligent resource management systems should enable reactive condition based planning. IT system interface models are necessary to prevent redundant data storage and to provide all relevant data and to facilitate new mobile assisting devices. In addition, technology has to deliver product data of actual product condition for reengineering, spare part production or renovation of mechanical and electronic components using future production technologies such as additive manufacturing [9,149]. In order to reduce downtimes of cost intensive products automation of operations is very important as well.

4.6.2. Solution approaches for overall reduction of through-life cost

Products can become intelligent cyber physical systems by RFIDs or integrated chipsets and communicate with cloud-based management services. Big data solutions are developed to enable collection and interpretation of all product related data, which is created during a life cycle. Thus, tracing of product changes through MRO could deliver knowledge that can directly be used to assist MRO planning and operation and to support product configuration management. Vice versa product data from design stage can be used to support inspection workflows in the MRO stage. In this context Augmented and Virtual Reality can be powerful tools to visualise product changes compared to CAD design. Intelligent information analysis and production technologies enable automation and specification of future digital MRO factories. Therefore adequate and efficient project management and workflow tools have to be created. Furthermore, acquired information in combination with advanced 3D scan and computer tomography data analysis systems (Fig. 33) [56,96] could identify single parts of a product and deliver a bill of material and product structure [41,156]. CAD parts in a database could be used for automated building of assembly models. In case of electronic

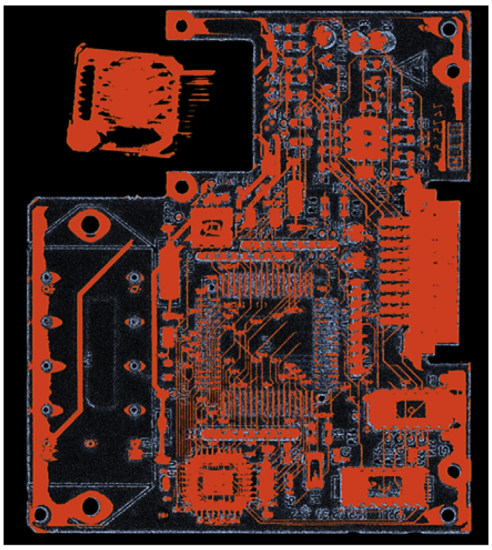

Fig. 33. Automated superposition of a 3D scan and a computer tomography of a printed circuit board.
Source: Fraunhofer IPK.

components schematics and layout plans could be reconstructed for repair and reproduction of spare parts. In this context quality control systems are able to realise automated 3D comparison of as-designed, as-produced, as-maintained, as-is and as-defined product geometries [55,81]. Product changes and operation can be visualised with Virtual Reality solutions augmented with inspection information. Virtual Reality also allows immersive training sessions for faster learning results.

Simulation of maintenance tasks for resource optimisation and cost estimating is becoming popular. Datta et al. [28] has demonstrated an application of discrete event simulation (DES) technique to study maintenance resource utilisation for an availability type defence contract. Alrabghi and Tiwari [4] have reported the dominance of DES for maintenance system simulation (61% of reported publications use DES). There is also use of hybrid modelling approaches where DES is integrated with a continuous element to represent time dependent degradation process. The other simulation techniques used include agent based simulation and continuous simulation.

4.7. Big data and data analytics

With the growing popularity of condition monitoring, prognostics, Internet of Things (IoT), Industry 4.0 and cloud computing, the volume of data available for continuous maintenance decision making has increased significantly. This large volume of relevant data is now referred as Big Data. The Big Data is defined to be high volume, high-velocity information assets, that comprises unstructured text, audio and video files [49]. It has a strong impact in almost every sector and industry [84]. Current methods in big data analyses are semantic data mining and integration of operational data. The key challenges in dealing with this high volume of data are: diversity in data types (variety), uncertainties in the data (veracity) and in some cases the speed of data collection and decision making (velocity) for maintenance purposes. In general, the Big Data complexity comes from data at a computational and system level. There is a lack of quantitative studies to understand the essential characteristics of the Big Data complexity. It is also observed that traditional data analytics techniques are not effective for the Big Data processing. Because of the fast changing Big Data (e.g., from continuous health monitoring across a number of assets within an enterprise), the analytics cannot rely on past statistics. Developing big data based maintenance decision support system will have significant system complexity due to the diversity of data (e.g., text data mining for the maintenance logs along with the vibration and temperature monitoring data from sensors). Management of the data across long life cycle and beyond is a major challenge in terms of governance, storage, access and supply chain collaboration. Fig. 34 presents a classification of Big Data. There is a need for value based analysis of the Big Data to answer specific domain questions and that will reduce the computational burden.

There are major research initiatives around the World that are interested in Big Data [84]: US Big Data research and development

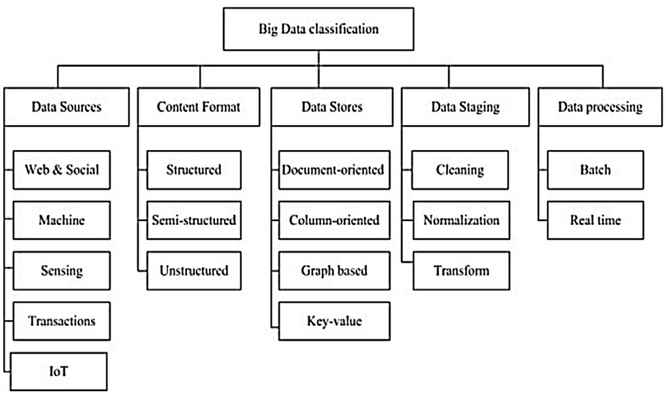

Fig. 34. Big Data classification [61].

initiative involving DARPA, DoD, NIH and NSF; UK Innovate UK and EPSRC initiatives across multiple industry sectors, EU Horizon 2020 focus on Big Data and Japanese through "The Integrated ICT Strategy for 2020". All these major initiatives are developing advanced tools and techniques to extract knowledge and insight from the data and that will help us to better understand the health of our machines and plan for the future spare parts and maintenance requirements.

The Big Data analytics could generate new knowledge by using the relationship of service events, component degradation and component design [25,108]. Applying the generated knowledge to the manufacturing environment, improves prediction accuracy of machine state and maintenance scheduling of the ERP system [97]. Ninety-five percent of big data is unstructured. Because of its heterogeneity and missing data structure the analysis of big data requires the development of new complex algorithms [49]. The faster the algorithms work, the better the distinction between valuable and trash data is, and the better the results will be [84]. To reduce costs of the extensive resources that are required for big data analysis cloud computing can be used, as shown in Fig. 35 [61]. This requires computing time and storage time that is actually utilised and has to be paid for only. Selecting appropriate cloud services for the data analytics is a challenge. Wang et al. [187] have presented an AHP based approach to select the cloud services based on computational cost and network communication load. In the CIRP keynote paper [50], the historical development of prognosis theories and techniques are summarised, and their future growth enabled by the emerging cloud infrastructure is projected. Techniques for cloud computing are highlighted, as well as the influence of these techniques on the paradigm of cloud-enabled prognosis for manufacturing and maintenance. The use of quantum computing offers further potential for reduction of computation time [73]. Shortened computation time can enable data analyses algorithm to evaluate data in real-time without the need for several hours of computing. In addition, the usage of advanced approaches of machine diagnostics [119] and stochastic optimisation algorithms [94] can gain their full potential when combining with big data.

Visualisation of the large volume of data is essential to support human analytical thinking and decision making for the continuous maintenance. The visualisation tools, also known as visual analytics, synthesise multi-dimensional information and knowledge from complex and dynamic data in order to support assessment, planning and forecasting. Adagha et al. [1] have presented a comprehensive analysis of the design of visual analytics (VA) tools and suggests four key attributes any VA tools should: provide multi user access to the data, support intuitive communication, support multiple and linked displays and track information flows between the users. Along with the tool development, there is also a requirement to use large visualisation spaces to display the large volume of heterogeneous data and support interaction with the users [138]. Design of a continuous maintenance approach (or service) at the early design stage of a complex engineering system can also benefit from VA tools [8]. The early design phase visualisation could assist in the design evaluation and creativity through exploration of alternative future scenarios with associated uncertainties.

4.8. Augmented reality for maintenance support and training

Augmented reality (AR) has the potential to become a major tool for the continuous maintenance, by overlaying and integrating virtual information on physical objects [32]. AR technology uses three fundamental techniques for the maintenance support: optical combination, video mixing and image projection. The AR tools are used in conjunction with a head mounted device (HMD) or a portable hand held device (e.g., a tablet) or a spatial display unit and a tracking system. Original ideas were developed in 1960s [161] and since then a steady progress has been made with the advancement of computing power and image analysis. Dini and

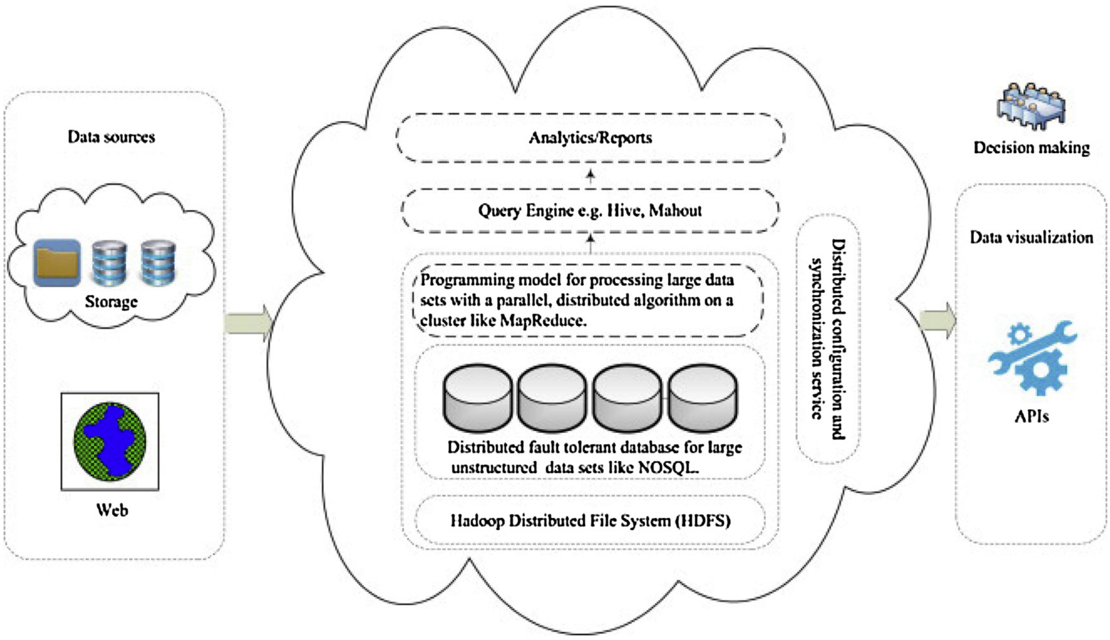

Fig. 35. Use of cloud computing for Big Data storage and analysis [61].

Mura [32] identified aerospace, automotive and industrial plant as the top three areas of AR application. Similarly, video mixing is the most popular approach for the AR solution development. HMDs are the most popular AR device used in the applications, followed by tablets. AR is used to support a maintenance task through a step-by-step guidance, diagnostics and inspection and training. Fig. 36 presents a research project to apply tablet based AR for NDT of pipelines [5]. To justify incorporation of AR technology to support aerospace maintenance, Suárez-Warden et al. [158] have presented a microeconomic analysis of the benefits of AR for aerospace maintenance assembly task. The microeconomic analysis incorporates the investment required, impact of downtime and the maintenance variable cost reduction.

In spite of the advancement of the AR technology, it is still not well established in industrial use yet. Current research on augmented reality on the shop floor deals with legibility of text that is projected on surfaces [34]. When information projected on surface in the shop floor is legible, it can assist the maintenance worker by providing valuable information about the maintenance task. Application of AR to assist maintenance tasks on the shop floor is dependent on the lighting conditions. We need to develop augmented reality technologies that can work consistently within industrial environment (both in poor light and open day light conditions). Regenbrecht et al. [139] has presented a number of early industrial applications of augmented reality where relevant information is overlaid on equipment for maintenance guidance. Nee et al. [122] provided an overview of augmented reality application across multiple manufacturing applications, including maintenance. The team identified tracking as a major trend in the augmented reality research. This is also very important for the maintenance research where we could overlay real time health data on equipment. Industrial applications of AR will also depend on the ease of AR content creation, especially related to the context of the real life object in focus, and adaptation of the AR response based on the object context [200]. The context aware AR system architecture is presented in Fig. 37, showing a rule based context reasoned working with a database of different contexts. The offline content creation and adaptation of the AR response is very important for continuous maintenance as the AR service could adapt based on the technician expertise. There is a need to extend the offline authoring to an interactive input interface to capture the technician feedback and reasoning for a maintenance decision on a physical object (e.g., repairing a hydraulic valve). In a very recent work, 'Cognitive Augmented Reality' is described as an automated AR content creation technique based on video analysis, adaptive feedback (Fig. 38) and real time learning [133]. Based on the limited case study, the technique has significant potential where Augmented Reality is applied to a number of maintenance training tasks. The training involves effective content management and efficiency of the AR technology to link the virtual information with

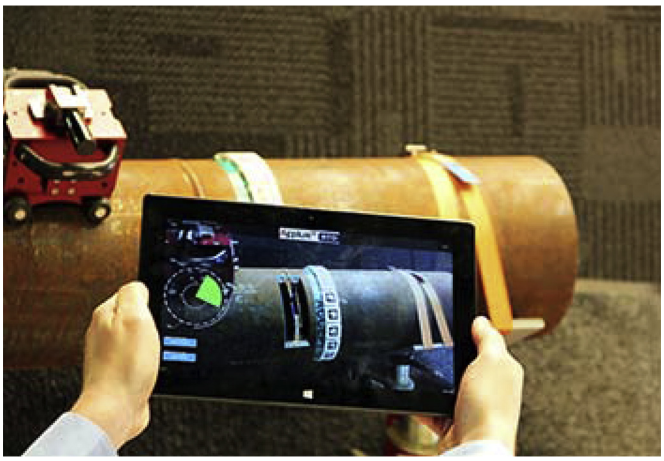

Fig. 36. Augmented reality applied to NDT for pipelines using a tablet device [5].

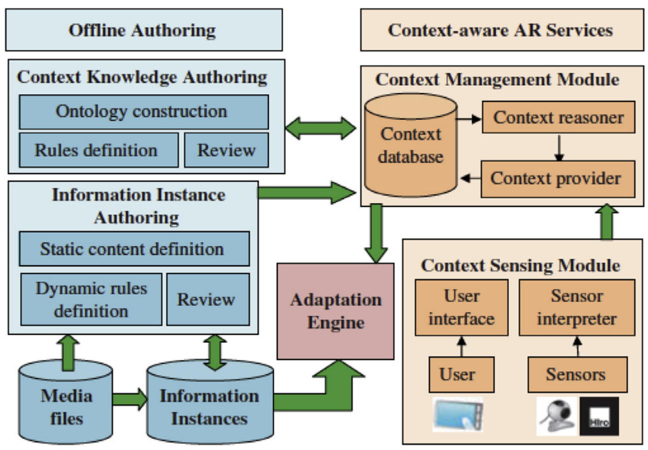

Fig. 37. Architecture for a context aware AR system [200].

Fig. 38. Examples from an automatically authored AR-manual: the half-transparent overlays (left) were automatically extracted from the reference sequence. The green colouring (middle) indicates a correct completion of the task, red a wrong posture or position. [133].

the physical objects, cognitive aspects of the training on the user learning and usability of the AR equipment. Schwald and de Laval [148] presented an early study on the effectiveness of AR technologies for maintenance training within industrial context. The research represented a scenario based context development that can provide step-by-step training for a maintenance task. The physical limitation of the HMD (e.g., weight, lack of complete wireless connection) and its impact on prolonged use by the maintenance technicians is highlighted as a major challenge at the time. This basic issue about the HMD still exists and as a result more mobile and handheld technologies such as tablets and smartphones are gaining popularity in industry. Neumann and Majoros [123] highlighted the difference between cognitive tasks and direct work piece manipulation tasks and their relationships to the level of attention required for different maintenance tasks. Use of AR would reduce manual interaction with the work piece and document search and study, but the training must address the 'level of attention' required for a maintenance task. This is particularly relevant for continuous maintenance of life critical equipment. De Crescenzio et al. [23] presented industrial case study of AR for aircraft maintenance training. The study developed a marker less AR technique supported by the training authoring system and proved its effectiveness within the industrial context. Webel et al. [189] discussed advantages of advanced AR equipment such as haptic feedback through a vibrotactile bracelet for rotational and translational movements. The study also highlighted the use of a training platform with AR based virtual elements allowing better measurement and evaluation of the trainee's performance with a level of detail that is not possible when performing the actual task without the virtual elements. The quality assurance and monitoring of continuous maintenance technician's performance are essential for complex engineering systems.

5. Future of continuous maintenance within the Industry 4.0 context

Cyber physical system (CPS) is the basis for Industry 4.0 or Internet of Things (IoT). Cyber physical systems (CPS) are the interconnection of physical objects through global or local data networks. They are the technological driver for collaboration in organisations. Cyber-physical systems gather the information that is the base for big data analyses. Objects autonomously communicate with each other to reach a common goal [147] within a CPS. Industry 4.0 provides an opportunity to collect more real time data about current state of machines, which can then be analysed using Big Data Analytics. Preventive maintenance events can be scheduled assuming smaller safety margins and the risk of unplanned failures will be reduced. The inventory level for spare parts can be reduced, because less safety stock for unscheduled events has to be stored. With the availability of current state of the systems, it would also be possible to plan spare parts availability across a geographic location to minimise the inventory cost. Further research is required to automate the maintenance planning activities that maximises the utilisation of available resources and availability of the systems at an optimum cost. Fig. 39 shows sources of data and communications within an Industry 4.0 based manufacturing plant for maintenance purposes. The obvious questions for future vision are:

- How maintenance is going to change in this highly connected industrial environment? Maintenance technology needs to adapt to the dynamic and agile manufacturing environment based on 'Industry 4.0'.
- How do we maintain more than one product in a system (e.g., twenty machine tools in a production line): maintenance of multiple machines simultaneously and optimisation of maintenance and operation schedules together.

According to these questions, Herterich et al. [64] have already assessed the impact of CPS on industrial services in Manufacturing. More precisely for the maintenance, they outlined the impact of CPS relates to "predict and trigger services activities", "remote diagnostics, "replace field services activities", "empower and optimise the field service and "information and data driven services". Based on the additional and real time data collected from the machines, efficiency and quality of the maintenance can be improved. In addition, Yokoyama [195] is investigating new

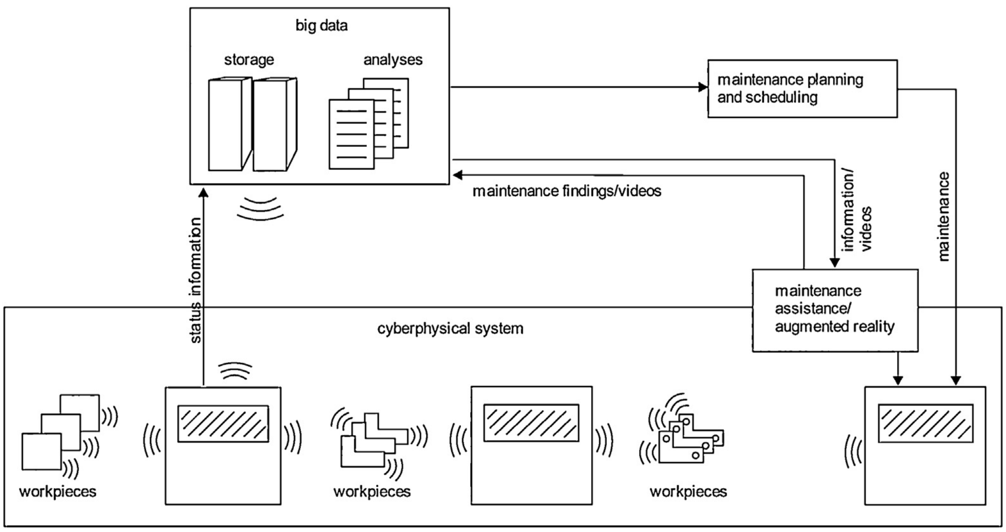

Fig. 39. A manufacturing plant based on Industry 4.0 showing the sources and communications of Big Data for maintenance purposes.

maintenance services in line with CPS through the "Smart Maintenance Initiative" advocated for Railway applications. An integrated maintenance platform will capture track irregularity and material condition data frequently by trains in operation and perform maintenance decision-making based on the condition of the individual track. CPS in the future will improve the ability to monitor individual systems and even components for maintenance.

In relation to fault prediction service, Xu et al. [194] are proposing an intelligent system based on IoT. Three major challenges in using IoT for the fault prediction of a machine group are: (1) communication of data from the IoT sensor network, (2) non-stationary and nonlinear fault prediction and (3) massive data processing. The IoT acts as an enabler for more efficient continuous maintenance, but the need for fundamental understanding of the degradation mechanisms and root causes for the failure modes remains unchanged. More globally, the cyber-physical system comprises of machines and work pieces that communicate autonomously with each other to reach the common objective of realizing the processing in production. Work pieces communicate their position and work progress, and machines communicate their status (e.g., working, waiting and mounting). The communication between machines and work pieces negotiates the point of time to start of the following production step. The resulting collaborative architecture is assimilated by Zuccolotto et al. [202] to an Artificial Immune Intelligent Maintenance System (AI2MS) which is biologically inspired. In a complementary way, with regards to life cycle consideration Denkena et al. [30] are using the term of gentelligent components to form new intelligent (maintenance) system. Gentelligent combines the attributes of genetics and intelligence in one adjective. Gentelligent components are able to feel, communicate and store information from their environment and thus act as autonomous intelligent individuals. In specific CPS-based maintenance, the information of machine status and condition monitoring information is sent continuously to a big data storage system (e.g., Cloud). Big data analysis algorithms watch and analyse all incoming data. Maintenance plans and schedules are derived based on the results of the big data analyses. Maintenance activities are scheduled depending on the machine condition. The maintenance plan is constantly adapted according to the machine status and work schedule. Lee et al. [99] are showing the impact of industrial big data analytics and CPS for the future maintenance and service innovation. Moreover, during execution of maintenance operations, information from the big database assists the maintenance workers. Videos or text information about maintenance task are provided to the worker by using innovative wearable devices meeting the needs of cloud manufacturing [59]. In turn the worker feeds back his or her findings and experience during the maintenance process into the database. In addition, spare parts can hand over all required data for the machine control unit automatically like an USB-device in a PC [35]. With time the increasing database enhances the accuracy of maintenance planning and information for augmented reality based maintenance worker assistance. Use of IoT as an enabler for continuous maintenance is still at its infancy. Fig. 40 shows a scheme for condition monitoring of engineering systems using IoT and cloud computing [192]. With the IoT and the cloud, condition data from various modules of an engineering system distributed across multiple locations can be collected and analysed together using cloud based data fusion and data analytics. The knowledge about the system health can then be fed back to the design team to achieve a closed loop design process.

There are still several key open issues in IoT for its adoption in the industry for the maintenance support [14]:

- Scalable, flexible, secure and affordable reference architecture for IoT solutions with components, devices and systems. Standards organisation, such as IEEE, 3GPP and ETSI have developed IoT reference architectures for network scalability and high traffic capacity [40]. Major industrial players are also introducing their own reference architectures.
- Addressing and naming of heterogeneous IoT devices within a network. Although there are several object naming services [38], there is a lack of knowledge about the robustness of the services.
- Supporting IoT object mobility, where the objects within a manufacturing system (e.g., products in an assembly line) move with time.
- Machine to Machine (M2M) communications between heterogeneous IoT devices [50] in terms of routing and end-to-end reliability is essential for efficient maintenance. In future, the network congestion has to be addressed in large scale IoT based systems.
- Intelligent and flexible Gateways (GWs) to connect heterogeneous devices and to cater for different characteristics of the devices.
- Remote device and data management [187] within a resource constrained environment of IoT (e.g., memory, energy constraints). Scalability of the device and data management is going to be a major challenge for the maintenance.
- Understanding traffic characteristics will be a major challenge to maintain an IoT enabled manufacturing system.
- Providing security for the IoT enabled systems is a critical issue. A series of properties, such as confidentiality, integrity, authentication, authorisation, non-repudiation, availability, and privacy, must be guaranteed for IoT based future systems [19,62].
- Standardisation of IoT devices and the communication interfaces is also essential to perform effective continuous maintenance [65]. Höller et al. argues for open standards to address the IoT scalability issue [65].
- Long term management of big data from the IoT devices for the maintenance purposes. Cloud based data storage is recently proposed to address this challenge [15].

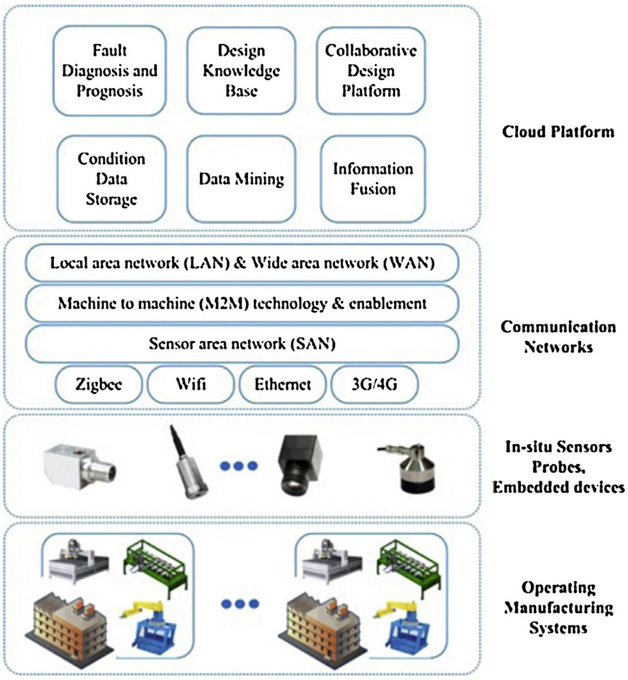

Fig. 40. A scheme of condition monitoring of engineering systems using IoT and cloud computing [192].

Common Internet protocols are unsuitable for the Internet of Things, because resources on devices are limited. Security keys and algorithms have to be developed that allow for the autonomous communication of devices with limited IT-resources [124]. Cyber security of the cyber-physical systems is a major topic of research in recent times. Zhang et al. [197] have identified three major areas of cyber security threats: aware execution layer (i.e., from sensors and actuators), data transport layer (i.e., from

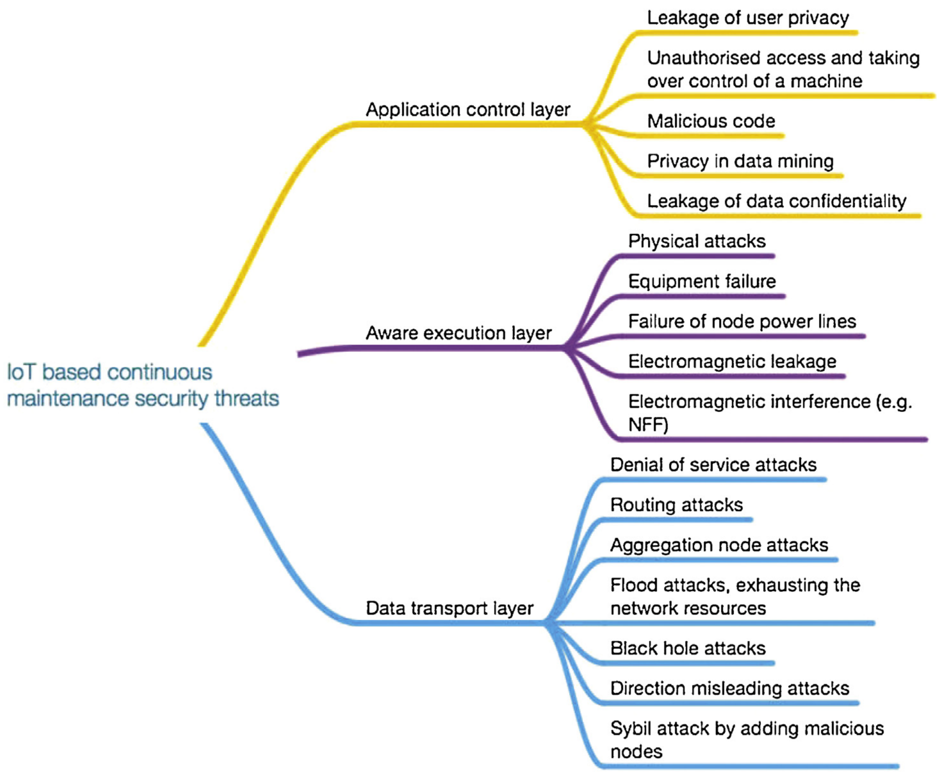

Fig. 41. Types of security threats for IoT based continuous maintenance (based on [114,197]).

network architecture) and application control layer (i.e., from user data storage) (Fig. 41). Knowles et al. [89] have presented a review of cyber security management techniques for industrial control systems. They have highlighted development of international standards (e.g., IEC 62443 for control systems and IEC 27000 series for information systems) to protect hardware and software. It is observed that legacy systems are a major challenge in the absence of built-in cyber security features. Olivier et al. [128] presented a novel software defined network (SDN) architecture for the IoT based systems. Continuous maintenance of complex engineering systems needs to protect the security features both at the hardware and software level and the SDN architecture could be very effective against any cyber threat.

Continuous maintenance also requires standardisation of IoT [117], Industry 4.0 and bid data analytics. The standards development is in its infancy and would require developments in both hardware and software. European Commission funded a number of IoT architecture development projects as first step for wider standardisation [91]. The scalability issue is addressed by several competing reference architectures: ETSI M2M, FI-WARE, IoT-A and IoT-6 [117]. Miorandi et al. [114] have highlighted a lack of standardisation in ontologies, data formats and data models to be used in IoT applications and in terms of its service level interfaces and protocols. Lack of standardisation of the IoT devices could increase the cost of continuous maintenance of the engineering systems. IoT software platforms are likely to converge into a few key players, such as Android and iOS, and this will have major challenges in integrating with the platforms used in the engineering systems. Similarly, the IoT communication technologies that are critical for an effective IoT based maintenance platform are [65]:

- Power line communications (PLC)
- LAN and WLAN
- Bluetooth low energy (Bluetooth Smart)
- Low rate, low power networks
- IPv6 over Low power Wireless Personal Area Networks
- IPv6 Routing Protocol for Low Power and Lossy Networks
- Constrained application protocol.

Continuous maintenance of an IoT enabled complex engineering system will require the IoT standards work with the existing maintenance standards such as PASS 55 (i.e., specification for optimal management of physical assets) and ISO 55000 (a family of standards: overview, principles and terminology).

Effective utilisation of the big data analytics and IoT for continuous maintenance will require resolution of the following challenges as well:

- Knowledge on 'smart intelligence' (e.g., control parameters) that would be necessary to control the maintenance of engineering systems.
- Knowledge to select the maintenance strategy for an integrated engineering system (e.g., service design).
- Ownership of data (including system and component design, bill of materials) is a major challenge to deliver the continuous maintenance across the supply chain. In the future, a 'data supply chain' with necessary reward structure has to be established to support the maintenance.
- Design and manufacture for continuous maintenance will require regular feedback to the designers and manufacturing engineers.
- Through-life data management across the life cycle of a engineering system would be essential. The data should also support detailed component level information to track degradation over time.
- Better integration of machine (e.g., robot) and human operators for collaborative maintenance solutions. This approach will address current challenges in autonomous maintenance.

6. Concluding remarks

Continuous maintenance is changing due to the business model evolution and the drivers such as 'optimising the through-life cost' or 'increasing the availability' of high value and long life products. Manufacturers are expected to guarantee performance over the contracted period and provide the maintenance service, often with a fixed price. Engineering for life is becoming popular to reduce the through-life cost. Manufacturers are now interested in better understanding of in-service degradation mechanisms of their components and systems; repair mechanisms; monitoring, diagnostics and prognostics; autonomous maintenance; obsolescence and integrated planning. In-service performance (e.g. degradation) feedback to design and manufacturing, although not covered in this keynote, is necessary to improve new products. Automating the feedback to the designers and manufacturing engineers will reduce current manual and expensive practice in industry and reduce cost. Developing condition-monitoring technologies to support legacy products that are not currently suitable for prognostics and remote maintenance is also very important to increase their remaining life.

The basic knowledge and skill sets required for the continuous maintenance research and practice are around the six foundations, and includes component and product level in-service degradation science and modelling based on material, design features and manufacturing process parameters for different environmental and use conditions. Manufacturers need to use this degradation information in the product development life cycle stages and integrate the organisation to implement an 'engineering for life' culture. The second most important skill in the future will be real time data capture, analysis and modelling of the 'big data' from the products in use within a 'highly connected' manufacturing and use environment so that the maintenance efficiency can be improved. Knowledge of uncertainty modelling will become more important for the data modelling. The other major knowledge and skill that are very relevant for the maintenance in the future are: autonomy for maintenance efficiency, repair technologies for new materials (e.g. composite repair) for resource utilisation and life extension and an integrated approach to obsolescence management. Globally, skills development for the continuous maintenance knowledge base is behind than that for the production technologies and systems. There is a significant lack of R&D investment in the area, especially considering the level of contribution from 'service and support' activities (often 50% of revenue) within the high value manufacturing sector.

Continuous maintenance technologies will enhance ability to assess health of components and products, develop autonomous maintenance solutions for efficiency and remote operation, visualise complex and uncertain data for decision making within an integrated maintenance planning environment and reduce the risks and cost. Advanced repair technologies are also important and are building on the advances in cleaning technologies, coating technologies and additive manufacturing. Self-healing technologies are still at its infancy and at the component level. Significant challenges have to be addressed to develop the ideas at the board level. Use of adaptive augmented reality in maintenance support will allow customised help and improve safety (i.e. less human error) and efficiency of the maintenance tasks. A cross-sector (e.g. manufacturing, construction, health care and IT) approach to research and technology development will allow mutual learning and reduce the R&D costs required to support continuous maintenance of high value products in the future. With the emphasis on using more and more life cycle data, secure data communication across the Extended Enterprise is essential for the maintenance to work in practice. The Extended Enterprise will also require a well-governed data supply chain, which is often missing in industry today.

With the foundations and technologies, there is a need to develop novel business models and contractual frameworks between the manufacturers, their customers and the supply chain to share the risks of guaranteeing the through-life performance. A stronger partnership between the manufacturer, their customer and the supply chain will be essential in the future. The partnership has to be supported by an internal organisational culture based on 'engineering for life' and servitisation.

Industry 4.0 is developing across the world and is the future context for continuous maintenance. It is observed that Internet of Things (IoT) and cloud computing are going to play a major role in the near future within the Industry 4.0 context. IoT on its own is only a major enabler of continuous maintenance, but effective utilisation of this technology for continuous maintenance depends on 'smart intelligence', service design, sharing of data across the supply chain, data feedback and management and better human and machine collaboration. Scalable architecture of the IoT based products; communication protocols and standards will be essential to support the future of continuous maintenance.

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